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Rehabilitation Prioritisation in Wastewater Collection Networks Using Multi-Criteria Decision Making (MCDM) Techniques

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Carolyn Charles

Abstract

The wastewater collection network serves as an important infrastructure for safely transporting wastewater from urban areas. Over time, pipe conditions can worsen, causing service disruptions and polluting water sources. Rehabilitation planning often lacks systematic approaches to prioritising pipes for rehabilitation.

Therefore, this thesis presents a Multi-Criteria Decision Making (MCDM) approach for prioritising wastewater collection pipes for rehabilitation planning. For this purpose, the Analytical Hierarchy Process (AHP) was used to weigh the criteria, including physical, operational, environmental, and economic criteria. Simple Additive Weighting (SAW) and Technique for Order Preference and Similarity to Ideal Solution (TOPSIS) were used for pipe prioritisation. Afterwards, the results were grouped into high, medium, and low rehabilitation priority levels using K-means clustering and GIS. This methodology was applied to a small study area in Nordre Follo municipality, Norway.

SAW and TOPSIS identified similar pipes for high rehabilitation priority, accounting for 11.9% and 13.3% of the total pipe length, respectively. These pipes were mainly concrete pipes installed before 1992. Both methods categorised all the pipes with historical failures as high rehabilitation priority, with this criterion receiving the highest weight. However, SAW and TOPSIS differed in their low- and medium-rehabilitation priority categorisations. TOPSIS categorised more pipes as low rehabilitation priority, resulting in fewer medium rehabilitation priority pipes, potentially underestimating their maintenance needs. Comparing Nordre Follo municipality's rehabilitation rate and the rehabilitation needs identified in this study, the municipality is advised to increase its rehabilitation activities.

However, due to insufficient data regarding historical failures, this technique does not accurately represent the municipality's main problems. With optimisation that includes more relevant data, the MCDM method is a valuable tool for systematically identifying and prioritising pipes for rehabilitation and asset management. This can facilitate municipalities in proactively managing assets and allocating resources efficiently, contributing to sustainable wastewater management.

Sammendrag

Avløpsnettet er essensiellt for trygg transport av både spillvann og overvann ut fra urbane områder. Grunnet ulike faktorer kan rørtilstaden forverres over tid, og forårsake driftsavbrudd og forurensning av vannkilder. Planlegging av rørrehabilitering mangler ofte systematiske metoder for å rangere hvilke rør som bør prioriteres for rehabilitering.

Denne masteroppgaven presenterer en systematisk tilnærming ved bruk av flermålsanalyser (MCDA) for å rangere avløpsrør for rehabiliteringsformål. Til dette formålet ble det definert økonomiske, fysiske, operative og miljøkriterier, som ble vektet ved bruk av Analytical Hierarchy Process (AHP). Simple Additive Weighting (SAW) og Technique for Order Preference and Similarity to Ideal Solution (TOPSIS) ble benyttet for å evaluere og rangere rørene. Resultatene ble videre gruppert inn i høy, middels og lav prioritet for rehabilitering ved bruk av K-means clusteranalyse og GIS. Denne metoden ble implementert på et lite caseområde på Kolbotn i Nordre Follo kommune.

Rørene som ble identifisert som høy prioritet for rehabilitering ved bruk av SAW og TOPSIS viste betydelige likheter. Disse utgjorde henholdsvis 11,9 % og 13,3 % av den totale rørlengden i nettverket. Hovedsaklig var disse rørene betongrør installert før 1992. Begge metodene kategoriserte alle rør med historiske svikt som høy prioritet for rehabilitering, ettersom dette kriteriet ble vektet høyest. TOPSIS kategoriserte imidlertid en større andel av rørene som lav prioritet for rehabilitering. Dette førte til at færre rør ble kategorisert som middels prioritet, og dermed potensielt underestimeres vedlikeholdsbehovet. Ved å sammenlikne rehabiliteringsraten til Nordre Follo kommune med det identifiserte behovet for rehabilitering, anbefales Nordre Follo å øke deres rehabiliteringsaktiviteter.

Imidlertid representerer ikke resultatene fra denne studien Nordre Follo kommunes hovedutfordringer, grunnet manglende data om historiske svikt i rør. Ved å inkludere andre relevante data med god kvalitet, kan denne MCDA metoden optimaliseres til et verdifullt verktøy. Dette kan tilrettelegge for kommuner i å proaktivt forvalte ledningsnettet og effektivt bruk av ressurser, som kan bidra til bærekraftig forvaltning av ledningsnettet.

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List of Acronyms

AHP	Analytic Hierarchy Process
ANN	Artificial Neural Networks
CI	Consistency Index
CR	Consistency Ratio
ELECTRE	ELimination Et Choice Translating REality
GIS	Geographic Information System
HDPE	High-Density Polyethylene
MADM	Multi-Attribute Decision Making
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MODM	Multi-Objective Decision Making
PE	Person Equivalent
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PVC	Polyvinyl Chloride
RI	Random Index
SAW	Simple Additive Weighting
TOPSIS	Technique for Order Preference and Similarity to Ideal Solution
WASPAS	Weighted Aggregated Sum Product Assessment

1. Introduction

As the population continues to increase, urbanisation keeps on growing, and the consequences of climate change become increasingly evident, it becomes more and more important to manage the urban water networks (Rostad, 2017). Due to various factors, the performance of urban water networks can deteriorate over time and cause disruptions in the water and wastewater services. This can further pollute surface water and groundwater sources, posing significant risks to public health and environmental sustainability (Brauset et al., 2021; The Association of Consulting Engineers in Norway [RIF], 2021). Additionally, operating and maintenance costs can increase as a result of these disruptions (Orhan et al., 2022). The estimated rehabilitation investment needs for wastewater collection networks in Europe have a significant gap to the actual investments being made (Tscheikner-Gratl et al., 2020). By postponing the rehabilitation of the wastewater collection network, this gap will continue to increase.

A known challenge for wastewater systems in Norway is the presence of ageing wastewater networks and pipes with low installation quality and lower-quality materials (Ministry of Health and Care Services & Ministry of Climate and Environment, 2024, p.30). Wastewater pipes installed between 1945 and 1970 in Norway are mainly locally produced concrete pipes with very low installation quality (Ødegaard, 2021, p. 398). The high leakage rates in wastewater collection networks can lead to wastewater infiltrating into drinking water pipes, thereby impacting water quality (Rostad, 2017, p.22). Likewise, leakage from the drinking water network can contribute to unnecessarily high loads on the sewage system. Additionally, stormwater from surface runoff and infiltration of groundwater are also contributing factors to the pipe load (Jørgensen & Rostad, 2023, p.48). In areas with combined sewer systems for both wastewater and stormwater, there is a heightened risk of infiltration by foreign water (Ministry of Health and Care Services & Ministry of Climate and Environment, 2024). The problems caused by foreign water in the wastewater collection networks can contribute to overflow operations, further polluting the water sources (Lindholm, 2017).

The renewal of wastewater collection networks in Norway encounters a backlog and requires significant investments to improve the overall condition of these networks (Rostad, 2017; Brauset et al., 2021). According to Brauset et al. (2021), the annual renewal rate needed in terms of pipe length for the wastewater collection networks was calculated to be at 0.88% in 2021, gradually increasing to 0.95% by 2035. The renewal rate goal is set at 1% by the Norwegian government for the wastewater collection network (Ministry of Health and Care Services & Ministry of Climate and Environment, 2024, p. 20) . However, the average renewal rate has only been between 0.6% and 0,7% in recent years (Statistics Norway, 2023), which is significantly lower than the recommended renewal rate. With this pace, it would approximately take 150 years to replace the existing water and wastewater pipelines in Norway (RIF, 2019). In 2022, only 38% of the municipalities in Norway had an acceptable pipe renewal rate corresponding to the municipality's needs, as reported by Jørgensen and Rostad (2023, p. 50). According to a report by Norwegian Water, the rehabilitation of the Norwegian municipal wastewater collection network, excluding the stormwater network, would require an investment of 85.7 billion NOK (Brauset et al., 2021).

Several criteria can influence the priority of pipe rehabilitation, highlighting the need for a tool that considers all relevant factors. Multi-Criteria Decision Making (MCDM) is a method that accomplishes this requirement perfectly. According to Tscheikner-Gratl et al. (2020) pipe selection for inspection and rehabilitation schedules are typically based on operator experience, customer complaints, or factors such as pipe age, material, or other operational conditions (Tscheikner-Gratl et al., 2020). According to Rønvik and Fjelle (2019), the use of support tools for renewal planning in Norwegian municipalities varies from municipality to municipality. However, they noted that the municipalities lack systematic approaches to planning pipe renewal for municipal urban networks (Rønvik & Fjelle, 2019, p.72). Chughtai and Zayed (2008) recommended defining priority areas for rehabilitation based on failure rates and structural defects, stating that randomly selecting pipes for system evaluation is costly. MCDM solves complex decision-making problems systematically and has gained attention in academic research as a powerful tool in different fields (Mardani et al., 2015). In the context of rehabilitation planning for wastewater collection networks, MCDM methods can support in deciding which part of the network requires rehabilitation. This approach provides a framework to evaluate different factors and prioritise the pipes accordingly. By implementing systematic prioritisation processes, municipalities can allocate their resources more effectively (Roghani et al., 2024). Therefore, MCDM techniques can contribute to more effective and sustainable management of wastewater collection networks.

Given the challenges encountered by the Norwegian wastewater collection network and the need for structured decision support tools for the municipalities, the main objective of this thesis is to employ MCDM techniques to prioritise wastewater collection pipes for rehabilitation, focusing on their risk of failure. Specifically, (1) identify factors that affect the performance of wastewater collection pipes, (2) determine the relative weights for the factors, (3) prioritise the pipes according to the MCDM techniques, (4) conduct a comparative analysis of the main results obtained from the MCDM techniques. For this purpose, Simple Additive Weighting (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) were employed as the MCDM techniques. At the same time, the Analytic Hierarchy Process (AHP) was used as a weighing technique. Furthermore, the K-means clustering technique and GIS were used to categorise the wastewater collection pipes into rehabilitation priority levels.

The rest of the thesis is structured into five Chapters: after this introduction, a literature review of existing assessment models for wastewater collection networks, factors affecting pipe deterioration, and the application of the MCDM techniques are presented in Chapter 2. This is followed by the methodology in Chapter 3, where the study area and a step-by-step procedure of the MCDM techniques are presented. Then, the main results are presented along with a discussion in Chapter 4, and is followed by the conclusion in Chapter 5.

2. Literature Review

Wastewater collection networks are essential components of urban infrastructure that have contributed significantly to urban development. These networks primarily transport wastewater from residential, commercial, and industrial areas, along with stormwater from surface runoff, to treatment facilities. Here, the wastewater is treated before it is released into the environment. There are two types of wastewater collection networks: combined and separated sewer systems. The combined sewer systems transport both stormwater and wastewater in the same pipe (Ødegaard, 2021, p. 31). In separate systems, the wastewater and stormwater are transported separately in two different pipes (Ødegaard, 2021, p.31). The proper functioning of the wastewater collection networks is essential for everyday life (Ana et al., 2009, p. 303).

2.1 Rehabilitation Planning Techniques

Marlow et al. (2010) defined asset management as follows:

> A combination of management, financial, economic, engineering and other practices applied to (physical) assets with the objective of maximizing the value derived from an asset stock over the whole life cycle, within the context of delivering appropriate levels of service to customers, communities and the environment, and at an acceptable level of risk. (Marlow et al., 2010, p. 1248)

Based on this definition, asset management for wastewater collection systems involves strategic planning of the maintenance and rehabilitation of the wastewater infrastructure. This process further includes economic consideration and risk management (Tscheikner-Gratl et al., 2020). Rehabilitation planning can be solemnly based on pipe condition assessment, or in combination with risk-based (Tscheikner-Gratl et al., 2020, p.4) or expert-based approaches (Salehi et al., 2018, p. 744). Risk-based methods evaluate the risk of pipe failure as a function of probability and consequence of failure (Baah et al., 2015; Tscheikner-Gratl et al., 2020). Expert-based techniques, such as prioritisation with Multi-Criteria Decision Making techniques, incorporate experts' experiments and judgements to make systematic evaluations. (Salehi et al., 2018, p.744).

Rehabilitation planning methods are based on the pipe condition assessment (Tscheikner-Gratl et al., 2020, p. 8). Several studies have assessed the pipe condition and performance of wastewater pipelines to find the relation between the factors affecting pipe deterioration and the pipe condition. Hawari et al. (2020) classified condition assessment models for wastewater collection networks into physical, statistical, and artificial intelligence (AI) models. Here, physical models describe the physical processes involved in pipe deterioration for wastewater collection pipes, statistical models are based on probability distribution, and AI models predict pipe deterioration by developing an algorithm to learn the deterioration patterns from inspection data (Hawari et al., 2020, p. 2).

2.1.1 Physical Models

Physical models are deterministic models that rely on the physical mechanisms of the deterioration process and do not account for uncertainties in this process (Hawari et al., 2020, p. 3–4). König (2005) developed an empirical model for estimating external corrosion of concrete sewer pipes called ExtCorr. This model considered soil moisture, soil aggressiveness, and the pipe's cement quality for estimation of the pipe condition. As part of the same project, Vollertsen and König (2005) developed an empirical model for internal corrosion prediction called WATS. This model describes the microbial and chemical transformation processes of organic matter in wastewater using differential equations.

2.1.2 Statistical Models

Statistical models describe the variability between the factors influencing pipe deterioration by predicting the relation between them (Rokstad & Ugarelli, 2015, p.791). Ariaratnam et al. (2001) used a logistic regression technique to predict the state of the sewer pipe condition, and prioritised regions of the sewer network for inspection. Kleiner et al. (2004) used a fuzzy rule-based Markovian process in a risk-based pipe condition assessment for large buried pipes. Chughtai and Zayed (2008) used multiple regression techniques to develop a structural condition prediction model for different pipe materials. Ana et al. (2009) used logistic regression to predict the condition of wastewater collection pipes in Leuven, Belgium. Furthermore, Rokstad and Ugarelli (2015) compared the statistical model GompitZ based on the Markov Chain model (Sægrov, 2006, as cited in Rokstad and Ugarelli, 2015, p.792) with a random forest model to classify and prioritise the wastewater collection network in Oslo municipality, Norway. Ghavami et al. (2020) combined GIS, Analytical Hierarchy Process (AHP), and data envelopment analysis to develop a systematic prioritisation of urban wastewater collection pipelines. This model is based on calculating the probability of failure using Bayesian Network and GIS, AHP and data envelopment analysis were used to determine the consequence of failure. Robles-Velasco et al. (2021) predicted pipe failure in wastewater collection networks by combining a logistic regression model with a genetic algorithm.

2.1.3 Artificial Intelligence Models

AI models are algorithm-based models that are considered to be data-driven, and often utilise machine learning and data analytic techniques (Hawari et al., 2020, p.4). Artificial neural networks (ANN) are a machine learning technique inspired by the human nervous system, and consist of interconnected artificial neurons organised in different layers (Sousa et al., 2014; Hawari et al., 2020). Khan et al. (2010) used two types of ANN models to predict the structural condition of wastewater collection networks and compared their accuracy. Sousa et al. (2014) compared the performance of two AI models, ANN and support vector machines, with logistic regression to predict the structural condition of wastewater collection networks. Similarly, Jiang et al. (2016) predicted the corrosion processes of concrete wastewater collection pipes by using ANN. On the other hand, Atambo et al. (2022) compared ANN with multinomial logistic regression to predict the condition of wastewater collection pipes for rehabilitation purposes. Hoseingholi and Moeini (2023) predicted pipe failure for rehabilitation planning using genetic programming. The results from genetic programming were compared with the ANN method, and it was concluded that genetic programming was better and more accurate than ANN.

The use of fuzzy logic has become popular to address uncertainty and imprecision, and is a computational method based on the degree of truth (Roghani et al., 2024). This way, fuzzy logic allows for the representation of gradual transitions between categories rather than enforcing strict differentiation (Hawari et al., 2020; Roghani et al., 2024). Li et al. (2019) developed three data-driven models to predict the sewer service life of concrete pipes based on estimating the corrosion rate. For this purpose, multiple linear regression, ANN, and an adaptive neuro-fuzzy inference system were used. Anbari et al. (2017) prioritised wastewater collection networks for inspection and rehabilitation planning using a fuzzy inference system based on the risk of failure. Here, Bayesian networks were used to calculate the probability of failure, and the weighted average method was used to calculate the consequence of failure. Similarly, Roghani et al. (2024) presented a method that integrated fuzzy logic and the Analytical Hierarchy Process (AHP) to evaluate the risk of wastewater pipe failures. With this risk-based model, this study prioritised pipes for rehabilitation by estimating the probability and the consequences of failure.

Other AI models, such as random forest and K-Nearest Neighbour, have also been used to assess sewer pipe condition. Laakso et al. (2018) predicted the wastewater pipe condition by using the random forest algorithm to plan pipe inspections. On the other hand, Nethra Betgeri et al. (2023) identified sewer pipes that needed repair or replacement by automating the identification process of wastewater pipes based on pipe condition. For this purpose, the K-Nearest Neighbour model was used to identify the pipes that needed urgent replacement based on historical repair data.

There have also been studies that have compared different machine learning techniques to find the most effective approach for the rehabilitation planning of wastewater collection networks. Nguyen and Seidu (2022) applied ten different machine learning algorithms, including random forest, K-Nearest Neighbour, Support Vector Machine, extra trees regression and ANN methods, to predict the condition of sewer pipes. The extra trees regression model performed best and was recommended as a pipe condition model for wastewater collection networks. Afterwards, Nguyen and Razak (2023) compared three hybrid machine learning models to predict the condition of wastewater collection pipes using environmental and physical factors.

2.2 Factors Affecting Pipe Deterioration

Wastewater pipes can deteriorate and cause pipe breakage and leakage due to the influence of numerous factors, typically involving chemical corrosion, structured degradation, or a combination of both (Ødegaard, 2021, p.32). When a wastewater collection pipe fails to perform as intended due to these issues, it is considered a pipe failure. Pipe failures can be divided into operational and structural failure (Hawari et al., 2020; Malek Mohammadi et al., 2020). Operational failure refers to the pipe's inability to fulfil its service requirements (Malek Mohammadi et al., 2020). Meanwhile, structural failure refers to the pipe's inability to maintain its shape and bearing capability (Tscheikner-Gratl et al., 2020, p.). According to Ana et al. (2009, p. 303-304), the structural failure of wastewater pipes happens in three stages: formation of the initial defect, pipe deterioration caused by the defect and structural collapse of the wastewater pipe. The factors that influence the structural degradation of wastewater pipes can be categorised into physical, operational and environmental factors (Davies et al., 2001). While municipalities typically have enough physical data, information on environmental and operational factors is often unavailable (Malek Mohammadi et al., 2020). Figure 2.1 presents some degradation factors considered in this thesis.

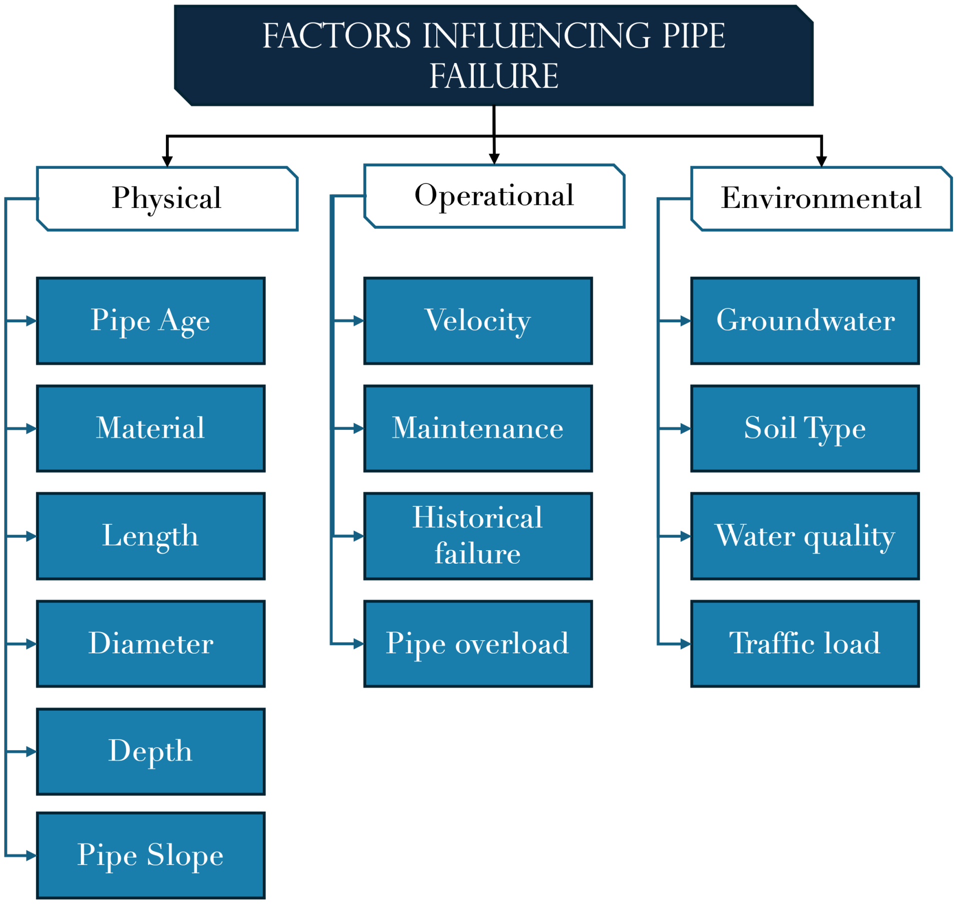


Figure 2.1: Classification of the factors influencing pipe deterioration leading to pipe failure into physical, operational, and environmental factors.

2.2.1 Physical Factors

Pipe Age

The physical factors are the characteristics of each pipe. The pipe age is an important physical factor that may not directly indicate pipe deterioration. However, older pipes are usually more prone to degradation due to being exposed to other external factors for a longer period of time (Angkasuwansiri & Sinha, 2013, p. 70). Ariaratnam et al. (2001, p. 163) and Laakso et al. (2018, p. 13) had a similar finding, indicating that the deterioration rate increases with the pipe service life. Furthermore, the installation and material quality of the pipes strongly relates to the pipe construction year, due to the influence of regulatory requirements and standards (Ødegaard, 2021, p. 398).

Pipe Material

Different pipe materials have different properties, and therefore are vulnerable to chemical and physical degradation. According to Khan et al. (2010) , the pipe material has the highest influence on the condition of sewer pipes. Historically, concrete is Norway's most commonly used pipe material for wastewater collection networks (Ødegaard, 2021, p. 378-380), with the concrete quality varying with the production year. Concrete pipes are vulnerable to chemical degradation in corrosive environments due to the development of sulfidgass (H_2S) in the pipes (Sulikowski & Kozubal, 2016; Ødegaard, 2021, p. 379-380). In recent times, plastic pipes have become the preferred material for various reasons, with high-density polyethylene (HDPE) and polyvinyl chloride (PVC) being commonly used for sewer systems. HDPE pipes are highly resistant to chemical deterioration, and can withstand impact damage better than other plastic materials in colder temperatures (Hafskjold & Sægrov, 2008; Ødegaard, 2021, p. 389). PVC pipes are lighter than HDPE and offer similar resistance to chemical deterioration (Ødegaard, 2021, p. 382). However, PVC has poor resistance to impact damage (Hafskjold & Sægrov, 2008). For both PVC and HDPE pipes, installation quality is a significant factor that limits their lifespan (Hafskjold & Sægrov, 2008; Ødegaard, 2021, p. 398).

Pipe Length

The length of the pipe, measured from manhole to manhole, influences pipe deterioration. The pipe condition decreases as the pipe length increases (Ana et al., 2009, p. 308). According to Lee (1998, as cited in Ana et al., 2009, p. 309), longer pipes tend to have more pipe joints, and defects on the pipe joints are commonly observed in wastewater pipes. Longer pipes are also more likely to encounter bending stresses (Hawari et al., 2020, p. 2) due to differential ground movements (Angkasuwansiri & Sinha, 2013, p. 72), and therefore have a higher potential for defects (Laakso et al., 2018, p. 13).

Diameter

Hawari et al. (2020, p. 2) stated that smaller pipe diameters are more prone to deterioration due to larger pipes having higher pipe thickness. Similarly, Ariaratnam et al. (2001, p. 164) found that the probability of pipe failure decreased with an increase in pipe diameter. Laakso et al. (2018, p. 13) suggested that pipes with larger diameters are often more carefully supervised during the installation, which may lead to better pipe conditions. Angkasuwansiri and Sinha (2013) noted that pipes with smaller diameters have a higher likelihood of blockages, due to the lower capacity in these pipes.

Pipe Depth

As the buried depth of the pipe increases, surface factors such as traffic load, maintenance activities, and root intrusions have less influence on pipe deterioration (Malek Mohammadi et al., 2020). Chughtai and Zayed (2008, p. 334–335) noted that traffic loads can affect pipe deterioration due to bending stresses caused by the traffic load. Additionally, due to the cold climate in Norway, the pipes need to be buried deeper than the ground freezing depth (Laakso et al., 2018; Nordre Follo Municipality, n.d., p. 19). However, when the depth increases past a certain level, the wastewater pipes can be more affected by soil pressure (Ana et al., 2009, p. 309). Malek Mohammadi et al. (2020) noted that deeper buried pipes may also experience deterioration due to being closer to the groundwater level. Laakso et al. (2018, p. 13) found that pipes installed at depths between 2m and 3m had better pipe conditions.

Pipe Slope

According to the US Environmental Protection Agency (EPA, 1992), flat slopes cause lower velocities in the wastewater pipes and can cause the formation of H_2S gas. This gas can further lead to the chemical deterioration of concrete pipes. Moreover, flat slopes can also contribute to pipe clogging as sedimentation accumulates in the pipes due to the low velocities (Ana et al., 2009, p. 309). Similarly, Laakso et al. (2018, p. 14) noted that negative and very low slopes were particularly harmful, as they could result in inadequate rinsing, sediment accumulation, and blockages. Meanwhile, steep slopes could lead to problems with high velocities in the pipes, causing physical erosion of the walls (Chughtai & Zayed, 2008; Laakso et al., 2018; Malek Mohammadi et al., 2020).

2.2.2 Operational Factors

Maintenance Quality

The operational factors relate to the functioning of the pipe. Malek Mohammadi et al. (2020) discussed the importance of having proactive maintenance strategies to minimise the impact of pipe deterioration and prevent failures. Similarly, Ariaratnam et al. (2001) and Hawari et al. (2020, p. 2) noted that improper maintenance plans and budget constraints faced by municipalities are significant factors in the deterioration of wastewater collection pipes. EPA (1992) also stated that poor maintenance quality of the sewer network could lead to an acceleration of pipe deterioration. According to Norwegian Water (n.d.), municipalities that prioritise maintenance of their pipe networks experience better pipe conditions than municipalities that delay maintenance.

Historical Failures and Pipe Overload

El Chanati et al. (2016) also stated higher historical failure indicates pipes with poor conditions. Given that several factors influence and contribute to historical failure, Zhou et al. (2009) stated that historical failure serves as the main indicator for describing the pipe condition. Chughtai and Zayed (2008, p.334–335) discussed the influence of pipe overload on pipe failure, stating that overflow from wastewater collection networks can pose health risks and monetary losses for communities while also burdening the municipalities. According to Kvaløsund and Birkeland (2024, p. 16), Oslo municipality uses pipe overload and basement flooding as primary factors for choosing geographical areas for wastewater pipe rehabilitation.

2.2.3 Environmental Factors

Groundwater Level and Soil Type

The environmental factors represent the surrounding conditions that affect the pipes. Davies et al. (2001), Chughtai and Zayed (2008, p. 334–335), and Malek Mohammadi et al. (2020) stated that the groundwater level could influence the pipe condition by infiltrating into the wastewater pipe. This washes soil particles, leading to reduced soil support along the pipe and weakening the support structure around the wastewater pipeline. Malek Mohammadi et al. (2020) also stated that wastewater pipes in regions with higher groundwater levels face a greater risk of failure than those with lower groundwater levels. Moreover, the type of soil that supports the pipe has different chemical and physical properties, which can contribute to pipe corrosion (Chughtai & Zayed, 2008, p. 335).

Water Quality

Wastewater quality depends on several properties and can therefore not be directly measured (Angkasuwansiri & Sinha, 2013, p. 75), but can usually be described by water quality parameters. As noted by El Chanati et al. (2016) and Hawari et al. (2020, p. 2), the chemicals, organic matter, and other substances present in the wastewater can internally corrode the pipe, leading to deterioration and breakage. Biological matter in the water can produce biofilms on the inner surface of the pipes. The growth of biofilm can lead to the formation of H_2S gas due to the bacteria creating anoxic conditions within the pipes (Ødegaard, 2021, p. 386). This can subsequently cause corrosion, particularly in concrete pipes.

2.3 Multi-Criteria Decision Making Techniques

Multi-Criteria Decision Making (MCDM), also known as Multi-Criteria Decision Analysis (MCDA), is a widely used tool to solve complex decision making problems in different fields (Mardani et al., 2015). The decision making process can be complicated when it involves evaluating multiple, usually conflicting, criteria with varying degrees of importance (Thakkar, 2021, p. 2). With MCDM techniques, the complex problem can be broken down into smaller pieces, or criteria, where each criterion is assigned weights representing their relative importance (Mardani et al., 2015, p. 517). Then, different options for the problem, or alternatives, are evaluated against each criterion before the evaluation is integrated to present an overall picture. This way, MCDM allows comparing different alternatives in a structured manner, considering qualitative and quantitative criteria to evaluate and prioritise alternatives (Gebre et al., 2021, p. 2). The MCDM process has more or less the same main steps: identifying the main goal for the problem, defining criteria that the alternatives are judged by, defining alternatives to achieve the goal and evaluating and prioritising the alternatives according to the defined criteria (Thakkar, 2021, p.24).

Over the years, multiple MCDM techniques have been developed. Based on their applicability, MCDM can be classified into two main categories, as seen in Figure 2.2: Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM) (Thakkar, 2021, p. 2). MODM methods evaluate continuous alternatives and are suitable for continuous optimisation problems (Thakkar, 2021, p.7). These methods can be used to design the best alternative when there are no predetermined alternatives. Instead, they optimise a set of objectives while considering constraints (Gebre et al., 2021). MODM methods can be classified further into mathematical programming models and heuristic methods (Gebre et al., 2021). Linear programming (LP), non-linear programming (NLP), and goal programming (GP) are examples of mathematical programming models (Gebre et al., 2021; Thakkar, 2021, p. 13). Simulating annealing (SA), genetic algorithm (GA), and non-dominated sorting genetic algorithm (NSGA) are examples of heuristic methods (Gebre et al., 2021).

MADM methods evaluate discrete alternatives determined in advance (Thakkar, 2021, p.7), and are suitable for prioritising and selecting the best alternatives (Gebre et al., 2021). Furthermore, MADM methods can be classified into pairwise comparison, outranking, distance-based, interaction, utility-based and other methods (Zayat et al., 2023, p.3). Pairwise comparison methods are based on evaluating the factors by comparing them directly with each other in pairs (Hummel et al., 2014; Taherdoost, 2017). The most popular pairwise comparison method is the Analytical Hierarchy Process (AHP) (Zayat et al., 2023, p. 3), which is explained more deeply in Section 2.3.1. Outranking

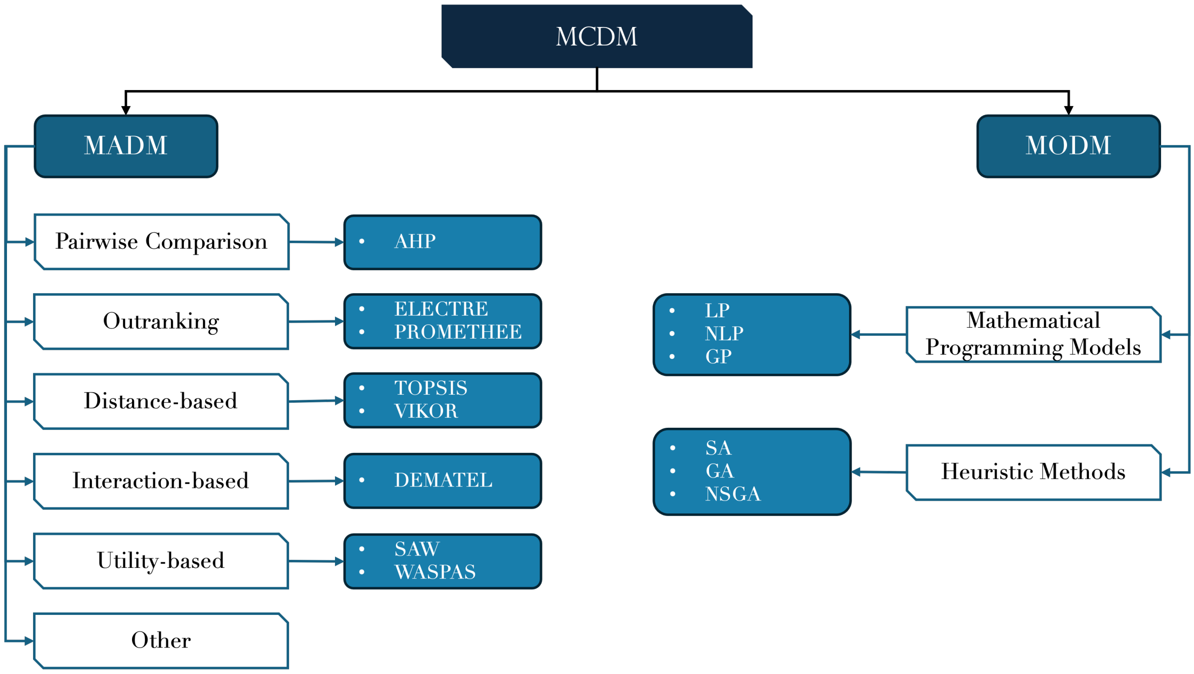


Figure 2.2: Classification of the MCDM techniques into MADM and MODM techniques with examples.

methods determine the superiority of one factor over others by establishing outranking relations (Zhou et al., 2009, p.4810). ELimination Et Choice Translating REality (ELECTRE) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) are two popular outranking methods. ELECTRE compares alternatives with each other and eliminates the alternatives that are not favourable (Thakkar, 2021, p.115–117). It focuses on identifying the best alternatives rather than ranking them in order from best to worst (Tscheikner-Gratl et al., 2017, p. 3). PROMETHEE, on the other hand, is an outranking method that ranks and chooses alternatives from conflicting criteria (Thakkar, 2021, p.119). Distance-based methods evaluate factors by measuring the distance to the ideal-best solution, where the factors closest to the ideal solution are favoured (Tscheikner-Gratl et al., 2017, p.5). Technique for Order Preference and Similarity to Ideal Solution (TOPSIS) is a popular distance-based method explained more deeply in Section 2.3.3. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) is another distance-based method that identifies, prioritises, and ranks alternatives to find the best compromise solution for a problem (Thakkar, 2021, p.129). Interaction-based methods assess the influence of the factors, acknowledging the impact on outcomes (Zayat et al., 2023, p.4). The Decision-Making Trial and Evaluation Laboratory (DEMATEL) is an example of an interaction-based method that visualises the relationship and interdependence between the factors (Thakkar, 2021, p. 139). Utility-based methods are based on the utility theory and determine the utilities associated with the factors (Zayat et al., 2023, p.4). Simple Additive Method is a utility-based method, further explained in Section 2.3.2. Weighted Aggregated Sum

Product Assessment (WASPAS) is a combination of SAW and the Weighted Product Method (Thakkar, 2021, p. 253). WASPAS evaluates the alternatives by aggregating the scores using both addition and multiplication (Thakkar, 2021, p. 253).

2.3.1 Criteria Weighting Techniques

The criteria weights are the foundation of the MCDM technique and significantly impact the overall outcome of the process. The characteristics of each weighting method can result in different weights assigned to the criteria, which can ultimately lead to ranking differences and affect the overall ranking order. (Ayan et al., 2023, p. 2). There are various weighting techniques, which can be categorised into subjective, objective, and combined methods (Ayan et al., 2023, p.2), as seen in Figure 2.3. Subjective methods are based on expert opinions, where people considered experts in their fields assign the criteria weights (Odu, 2019, p.1450). An example of a subjective weighting method is the pairwise comparison method Analytical Hierarchy Process (AHP), explained further in Section 2.3.1. The Direct Rating Method is another subjective weighing method where the weights are directly assigned to each criterion based on the expert's judgment (Odu, 2019, p.1451). Other techniques, such as the Fully Comparative Method (FUCOMB) (Ayan et al., 2023, p) and Stepwise Weight Assessment Ratio Analysis (SWARA) (Thakkar, 2021, p.281-288), are examples of other subjective weighting techniques.

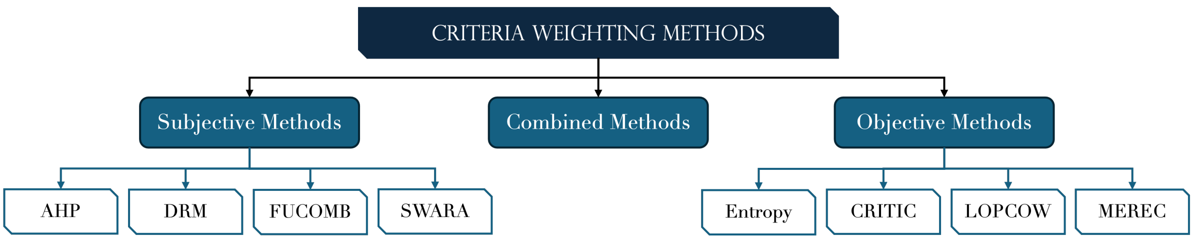


Figure 2.3: Categorisation of criteria weighting techniques into subjective, objective and combined methods with examples.

In contrast to the subjective method, objective weighting methods are based on factual data and use mathematical algorithms to assign criteria weights (Ayan et al., 2023, p. 2). The Entropy weighting technique is an example of an objective weighting method based on the concept of entropy from information theory (Shannon, 1948, as cited in Wu et al., 2022, p. 7). This method measures the degree of variation in the data available for each criterion and determines the weight without relying on additional subjective information (Thakkar, 2021, p. 165–168). Other techniques, such as CRiteria Importance Through Intercriteria Correlation (CRITIC) (Odu, 2019, p.1456), Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) (Dua et al., 2024, p.133-134), and Method based on the Removal Effects of Criteria (MEREC) (Dua et al., 2024, p.133), are also examples of objective weighting techniques.

Combined weighting methods combine the subjective and objective weighting methods, ensuring that both experts' opinions and data information are considered (Odu, 2019, p. 1450–1451). The use of combined weighting techniqes have become more popular in the recent years. Bayat et al. (2022) evaluated the performance of the surface water distribution network using the WASPAS MCDM technique, where the weightings were obtained by combining AHP and Entropy weights. Xu et al. (2016) analysed the development strategy of China's rural drinking water supply using TOPSIS, with combined AHP and Entropy for weighting. Wu et al. (2022) assessed the flood risk of the Poyang Lake basin in China with MCDM analysis by combining AHP and Entropy weighting techniques.

Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) was developed by Saaty (1970, as cited in Thakkar (2021, p. 33)) and is one of the most used MCDM techniques (Mardani et al., 2015, p. 525). AHP is a subjective pairwise comparison method based on experts' experience and opinions, and is commonly used as a subjective weighting technique (Zhou et al., 2009).

Several studies have applied AHP to determine the criteria weights. Zhou et al. (2009) developed a fuzzy-based pipe condition assessment model using PROMETHEE II, where the weights for the criteria were determined using AHP. El Chanati et al. (2016) presented four MCDM-based assessment method for water distribution pipes. In this study from Qatar, the relative weights using AHP, Analytic Network Process (ANP), Fuzzy AHP and Fuzzy ANP were compared. The weights obtained using these methods had highly similar outcomes. Hassoun Nedjar et al. (2023) applied AHP to the water distribution network to develop a decision support tool using 17 criteria for rehabilitation planning. In this study from Algeria, both the criteria and the alternatives were evaluated using AHP.

Some disadvantages of the AHP method are that with a large number of criteria, the number of pairwise comparisons increases (Thakkar, 2021, p. 61). As a result, this method can be very time-consuming, depending on the number of criteria defined. Since AHP is based on expert judgments, the criteria will be influenced by uncertainty and subjectivity (El Chanati et al., 2016).

2.3.2 Simple Additive Weighting

Simple Additive Weighting (SAW), also known as the Weighted Sum Method (WSM), is an MADM method first developed by Churchman and Ackoff (1945, as cited in Vafaei et al., 2022, p. 1232), and is one of the oldest and most commonly used MADM techniques (Taherdoost, 2023). The basis is to calculate the weighted average for each alternative based on the weights assigned to each criterion (Thakkar, 2021, p. 27). The alternative with the highest weighted sum is considered the optimal alternative (Taherdoost, 2023). SAW was chosen for this study due to its simple nature and straightforwardness, making it easy for municipal workers to understand this method. Additionally, there is no need for complex programming to apply this method. It can be applied easily using Excel.

Baah et al. (2015) created a risk assessment model using SAW and GIS to prioritise wastewater collection pipes for rehabilitation and maintenance. In this study, rehabilitation planning was based on the risk and consequences of pipe failure. Tscheikner-Gratl et al. (2017) compared the applicability ELECTRE, AHP, SAW, TOPSIS and PROMETHEE for integrated asset management of water systems in Austria. First, the study evaluated individual interconnected infrastructure networks, including sewer, water, gas, and road networks, using these five MCDM methods. Then, they combined the results to identify and prioritise street sections for rehabilitation

Even though the SAW method helps rank the alternatives and is simple to implement, it also comes with some limitations. The SAW method is not defined for negative criteria and requires all the criteria to be positive (Taherdoost, 2023, p.22-23). Furthermore, SAW prefers higher values of criteria, treating the criteria as maximising in nature (Thakkar, 2021, p. 32). Therefore, the minimising criteria have to be converted to maximising criteria.

2.3.3 Technique for Order Preference and Similarity to Ideal Solution

Technique for Order Preference and Similarity to Ideal Solution (TOPSIS) is an MADM method developed by Hwang and Yoon (1981, as cited in Thakkar, 2021, p. 83). TOPSIS evaluates the alternatives based on the Euclidean distance to determine the proximity to the ideal-best alternative and the distance from the ideal-worst alternative (Orhan et al., 2022, p. 840). The ideal-best alternative represents the best possible alternative with all the best values from each criterion. Meanwhile, the ideal-worst alternative represents the least favourable alternative. According to TOPSIS, the optimal alternative is closest to the ideal-best alternative and farthest to the ideal-worst alternative (Thakkar, 2021, p. 83).

Salehi et al. (2018) prioritised pipes and the zones related to the pipes, to rehabilitate the water distribution network using TOPSIS. This study discussed how TOPSIS would be helpful in MCDM problems with many criteria and alternatives for decision-making, such as in water distribution system rehabilitation. Wu and Abdul-Nour (2020) compared AHP, TOPSIS, ELECTRE III and PROMETHEE II to prioritise sewer network plans as a group decision. The objective was to identify the most suitable MCDM method that accurately represented the decision makers' preferences in group decision problems. Orhan et al. (2022) used the MCDM techniques Entropy, ELECTRE, and TOPSIS to prioritise pipe regions for rehabilitation in wastewater collection networks. This study from Turkey considered 26 criteria that were weighted using the Entropy technique. Park et al. (2023) prioritised water distribution networks in South Korea for rehabilitation purposes at a regional level, combining the TOPSIS and Entropy methods. In this study, they included data on complaints about water quality and leakage from customers in the assessment. Another study by Pokhrel et al. (2023) assessed the performance of urban water systems, including water, wastewater and stormwater networks, by applying TOPSIS with AHP weights. In this study, TOPSIS was employed to analyse data from various key performance indicators related to the different components of the urban water systems.

Some limitations of the TOPSIS method is that it requires all the data for different criteria to be expressed in the same measurement unit. Therefore, the data must be converted to a common scale (Park et al., 2023, p. 719). Furthermore, TOPSIS treats the criteria as monotonically increasing or decreasing (Thakkar, 2021, p. 91), meaning that higher or lower values of the criterion, depending on their nature, are consistently considered more favourable. Therefore, the criterion cannot increase in importance and decrease after a certain threshold.

2.4 Delimitation of this Thesis

From the literature review, it is clear that pipe prioritisation of wastewater collection networks is important to ensure that the network functions reliably and that the resources are managed effectively. Several studies have successfully applied MCDM techniques to prioritise the pipes, individually or regionally, in water distribution systems (Zhou et al., 2009; El Chanati et al., 2016; Salehi et al., 2018; Hassoun Nedjar et al., 2023; Park et al., 2023). However, limited studies have been conducted prioritising pipes for planning the rehabilitation of wastewater collection networks.

Nevertheless, despite the use of SAW, TOPSIS and AHP for urban water systems, studies on these MCDM applications in wastewater collection networks are limited. In addition, the use of K-means clustering to group the pipes into rehabilitation priority groups is also limited. As previously mentioned, decision making tools are not commonly used in Norwegian municipalities to plan pipe renewal. Therefore, in this thesis, MCDM techniques were applied to prioritise wastewater collection pipes for rehabilitation planning in Nordre Follo municipality, Norway. Specifically, SAW and TOPSIS were used for pipe prioritisation, while group AHP was used for weighting the criteria. These MCDM techniques were selected due to their simple application and the lack of necessity for complex algorithms. The assessment included physical, operational, and environmental pipe deterioration factors, as well as economic factors influencing the pipe rehabilitation planning. These factors were defined as the criteria for this study, and the alternatives were each individual pipe in the network. This way, each pipe was evaluated in accordance with the criteria. Moreover, the K-means clustering technique was applied to categorise the pipes into rehabilitation priority groups, which were visualised later in GIS.

In alignment with the thesis objective, the following research questions will guide this thesis:

1. What is the relative weight of the criteria in rehabilitation planning for wastewater collection pipes, considering both the available data and experts' opinions?

2. How does the application of SAW and TOPSIS affect pipe prioritisation in the study area in Nordre Follo municipality?

3. What are the characteristics of pipes prioritised for rehabilitation?

4. How can pipe prioritisation with MCDM contribute to the proactive management and preventative rehabilitation planning of the Norwegian wastewater collection networks?

The novelty of this thesis is prioritising wastewater collection pipes for rehabilitation by combining AHP weights with SAW and TOPSIS methods, and categorising the pipes in rehabilitation priority groups using K-means clustering and GIS. This thesis focuses on only evaluating and prioritising wastewater collection pipes, and will not include other essential parts of the wastewater collection networks.

3. Methodology

The research methodology started with a literature review of the existing rehabilitation planning tools and assessment models, factors affecting the performance of wastewater collection pipes, and MCDM techniques. From the literature review, the relevant MCDM methods and criteria were determined based on the data available for the case study in Nordre Follo municipality. Afterwards, the data was cleansed and prepared for the application of the SAW and TOPSIS techniques. In Figure 3.1, the flowchart of the methodology is presented, showing the different steps of the methodology used in this study.

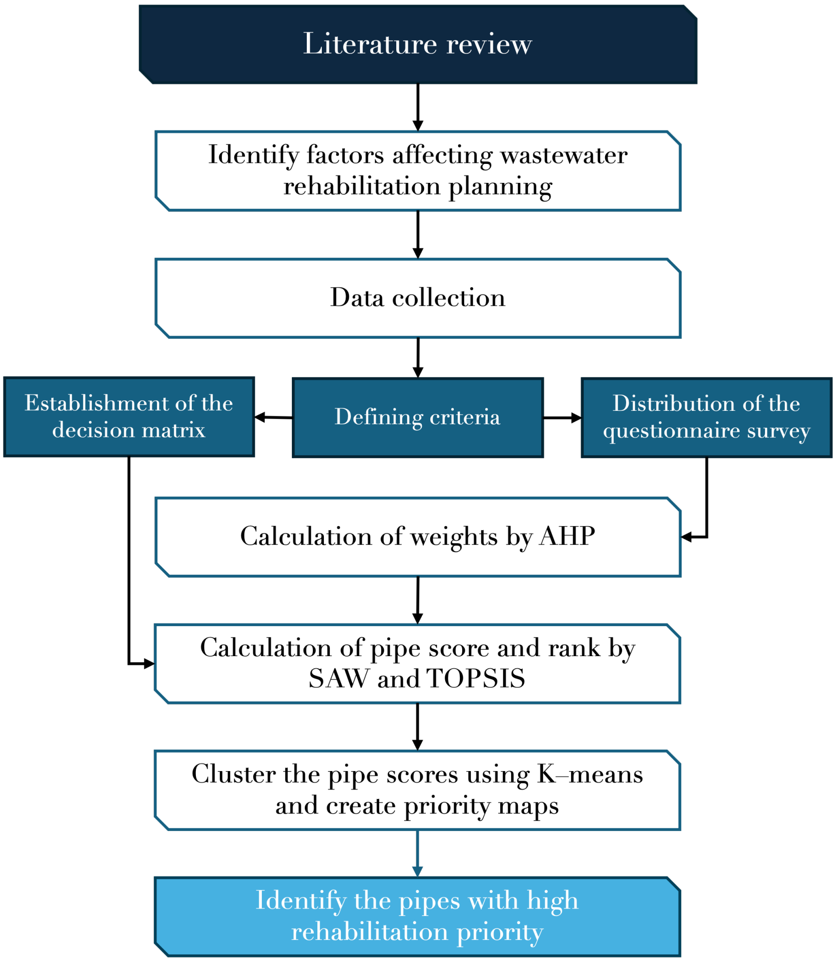


Figure 3.1: General flowchart of the research methodology.

3.1 Case Study

SAW and TOPSIS were applied to data provided by Nordre Follo municipality to evaluate the risk of failure for each pipe of the wastewater collection network, and categorise them according to their criticality for replacement.

Kolbotn is an urban area in the Nordre Follo municipality in Akershus county, located in the southeast part of Norway. The study area, presented as the blue region in Figure 3.2 and 3.3, is located in the eastern part of Kolbotn and is a part of the Augestadbekken stream's catchment area. This case study covers a network that serves approximately 3000 persons, consisting of 135 pipes with a total length of 6431m. The average pipe age of the network is 36 years, with the oldest pipes dating back to 1958 and the youngest pipes being installed in 2020. Approximately 60% of the pipes were constructed before 2000. Generally, the older pipes are made of concrete, while the newer pipes are mainly PVC. All the pipes have diameters between 100mm and 250mm. In this particular area, historical failure is represented as pipe blockages, with 17 pipes, constituting 12% of the pipes, being affected. Based on the cost estimation for pipe renewal provided by Nordre Follo municipality, the total renewal cost for this particular network is estimated to be 162,6 million NOK. This is a very rough estimation based on the pipe length that needs to be replaced. It excludes any sheet piling, which may be relevant for some of the areas in this study, particularly areas with clay-rich soil.

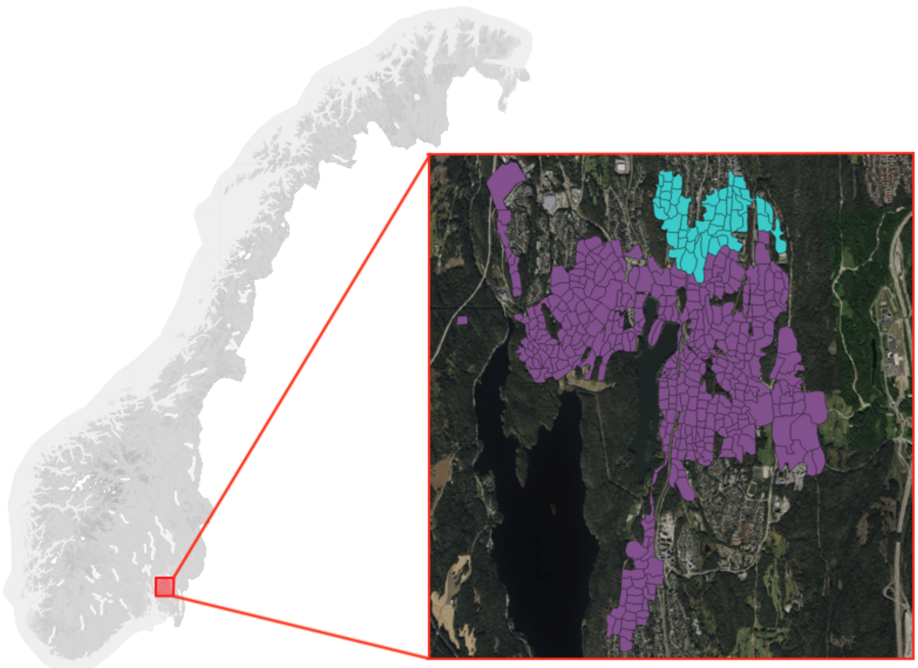


Figure 3.2: The placement of the study area in Nordre Follo municipality in Norway. The study area (in blue) is part of the bigger network of Kolbotn (in purple). The map of Norway is sourced from Kartverket (n.d.)

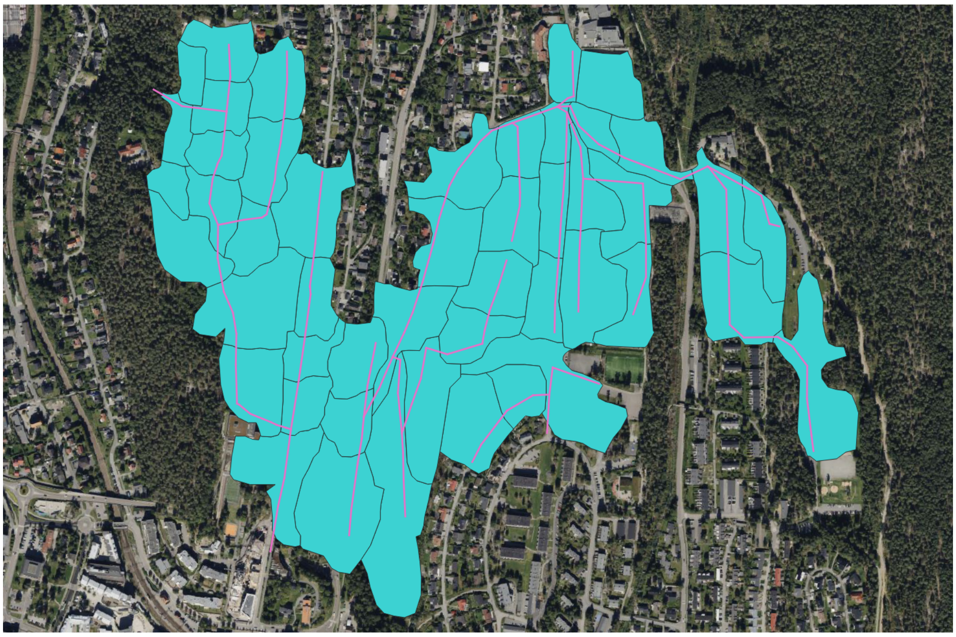


Figure 3.3: The study area for this case study in Nordre Follo municipality with a map of the wastewater collection network.

3.1.1 Defining Criteria for Pipe Rehabilitation

Based on the literature discussed in Secion 2.2, a list of the most common factors affecting the degradation and rehabilitation planning of wastewater collection pipes was prepared. From this list, the criteria for this study were selected based on the applicability and data availability of the Nordre Follo wastewater collection network. As shown in Table 3.1, the specified criteria were grouped into four main categories: physical, operational, environmental and economic factors. The physical factors represent the physical characteristics of each pipe. These factors do not change from the time of pipe installation until the next pipe replacement. From the physical factors, the criteria material, diameter, length, buried depth, slope and pipe age were selected (see Table 3.1). The operational factors represent the aspects related to how the pipes are used, maintained, and operated within the network. Hence, this category included the criteria maximum and minimum velocity, pipe overload rate, historical failure and person equivalent. The environmental factors represent the surrounding environmental conditions affecting the pipes, including the traffic load above the pipe. Lastly, the economic factors are the factors that influence the prioritisation of pipes for rehabilitation.

Table 3.1: Selected criteria and their definitions based on factors affecting the deterioration of wastewater collection pipes and rehabilitation planning.

Factor	Criteria	Description
Physical	Pipe age	The age of the pipe, based on construction year.
	Diameter	The diameter of the pipe.
	Length	Length of the pipe.
	Buried depth	The depth of the buried pipe.
	Slope	The slope of the constructed pipe.
	Material quality	Material quality of the pipe, based on the pipe material.
Operational	Maximum velocity	The maximum velocity simulated for the pipe.
	Minimum velocity	The minimum velocity simulated for the pipe.
	Pipe overload rate	Number of times the pipe capacity has been exceeded.
	Person equivalent	Person equivalent connected to the pipe.
	Historical failure	The number of failures or repairs due to blockage, leakage, breakage, among others.
Environmental	Traffic load	Traffic intensity on the street above the pipe.
Economic	Pipe renewal cost	Cost of pipe repair and/or replacement.

3.1.2 Establishment of the Decision Matrix

To build the decision matrix for calculations, the data regarding the pipes' physical factors and person equivalent (PE) was extracted from the MIKE URBAN model of Nordre Follo municipality's wastewater collection network. The pipe age was determined from the pipes' construction year, and the buried depth was calculated based on elevations obtained from the MIKE URBAN model. Based on the literature (Ødegaard, 2021; Hafskjold & Sægrov, 2008; Sulikowski & Kozubal, 2016) and experience from Nordre Follo municipality, the pipe material was converted into material quality, as shown in Table 3.1. Thereby, concrete was classified as low quality, PVC as high, and HDPE as very high quality. The material quality was primarily evaluated based on material properties and their chemical degradation properties.

The operational factors, including pipe overload, minimum velocity, and maximum velocities, are simulated using data from the municipality's MIKE URBAN model, incorporating precipitation data from 2023. Pipe overload rate and maximum velocities are simulated values based on the entire year's data, whereas the minimum velocities were derived from precipitation data specifically for May 2023, which was considered a dry period. Even though the wastewater collection network in this particular area operates as a separate system, precipitation data were necessary to include in the modelling. This is due to the presence of extraneous water in the wastewater collection pipes, which causes the degree of pipe fillings to fluctuate in response to the varying amounts of runoff water and groundwater.

The pipe overload rate was determined by first extracting the number of times the pipe exceeded its capacity from the MIKE URBAN model. The overload rate was then calculated by dividing the number of times a pipe was overloaded during 5-minute periods by the total number of such 5-minute periods. The historical failure was obtained from the Gemini VA database. Data regarding the traffic load was acquired by categorising the roads above the pipes according to their traffic intensity. High-intensity roads corresponded to high traffic loads. The cost of pipe renewal is estimated using cost estimations provided by Nordre Follo municipality and is determined by the road type above the pipe. If the road was classified as a main road, the cost estimation of 30 000 NOK per running meter was applied. Otherwise, 25 000 NOK was used to estimate smaller roads and areas excluding roads.

All of the data was thoroughly reviewed for consistency. The AI tool ChatGPT was used to develop Python scripts for data cleansing and establishment of the final decision matrix. Any incomplete data was supplemented by referring to other accessible resources or estimated based on information available for nearby pipes. For example, if the pipe age was missing for a particular pipe, it was assumed to be the same as that of the connecting pipes. Any negative values were set to zero, to accommodate the limitations of negative values in the SAW method. Afterwards, all criteria were classified into benefit and cost criteria according to the risk of pipe failure, as seen in Table 3.2 .

Benefit criteria are those for which higher values are favoured (Vafaei et al., 2022, p. 1232), meaning that a higher value corresponds to a higher score. In contrast, cost criteria favour lower values. In this thesis, the pipes are evaluated based on their risk of failure. This means that the higher the score assigned to a pipe, the greater the risk of pipe failure. As seen from Table 3.2, pipe age, length, maximum velocity, pipe overload rate, person equivalent, historical failure, and traffic load are identified as benefit criteria. For these criteria, a higher value means a higher risk of failure. Meanwhile, diameter, buried depth, material quality, slope, minimum velocity, and pipe renewal cost are identified as cost criteria. For these criteria, a lower value signifies a higher risk of failure. The pipe renewal cost does not affect the risk of pipe failure but affects the rehabilitation urgency level. For example, if a pipe has poor conditions but the rehabilitation costs are high, the decision to rehabilitate this pipe might be postponed because of the high costs. This means that the risk of failure may be deemed acceptable when compared to the high expense of rehabilitation. Therefore, pipe renewal cost was classified as a cost criterion.

Table 3.2: Classification of criteria into benefit and cost criteria with corresponding data types. Here + represents the benefit criterion, and − is the cost criterion.

Criteria	Data Type	Risk of Failure
Pipe age	Quantitative	+
Diameter	Quantitative	-
Length	Quantitative	+
Buried depth	Quantitative	-
Material quality	Qualitative	-
Slope	Quantitative	-
Maximum velocity	Quantitative	+
Minimum velocity	Quantitative	-
Pipe overload rate	Quantitative	+
Person equivalent	Quantitative	+
Historical failure	Quantitative	+
Traffic load	Qualitative	+
Pipe renewal cost	Quantitative	-

Moreover, as seen from Table 3.2, all the criteria except the material quality and traffic load had quantitative data. Based on the Table 3.3 (Thakkar, 2021, p.30), the qualitative data for material quality and traffic load were quantified. This quantification transformed all the qualitative criteria into benefit attributes.

Table 3.3: The rating scale used to quantify the qualitative data (Thakkar, 2021, p.30).

Benefit Attributes	Score	Cost Attributes	Score
Very low	1	Very low	9
Low	3	Low	7
Medium	5	Medium	5
High	7	High	3
Very High	9	Very High	1

3.2 Assigning Criteria Weights

To perform the MCDM techniques, weights must be assigned to the selected criteria. Therefore, the criteria were weighted using the AHP method, which is presented in Figure 3.4.

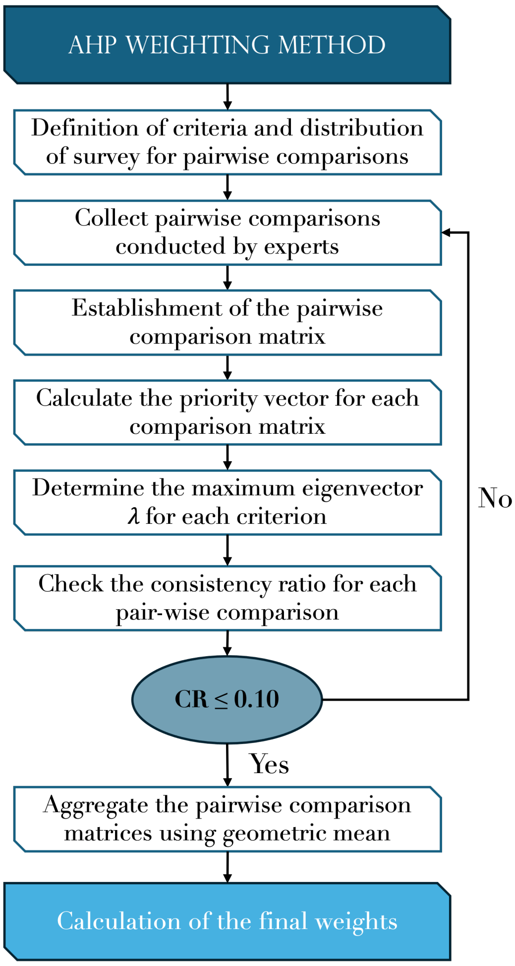


Figure 3.4: The flowchart for the AHP weighting method used in this thesis.

To determine the weights with AHP, experts were asked to compare and score the defined criteria according to their importance in rehabilitation planning for wastewater collection pipes. The experts' opinions were collected using a questionnaire prepared in Google Forms and distributed among university professors, municipal engineers, and consultants with expertise in wastewater collection networks in Norway. The purpose of the questionnaire was to identify the degree of importance of each criterion with respect to rehabilitation planning and deterioration of wastewater collection pipes. Due to the number of criteria, 78 pairwise comparisons were required. An example of the questionnaire setup is provided in Figure 3.5, and the whole questionnaire is provided in Appendix A.

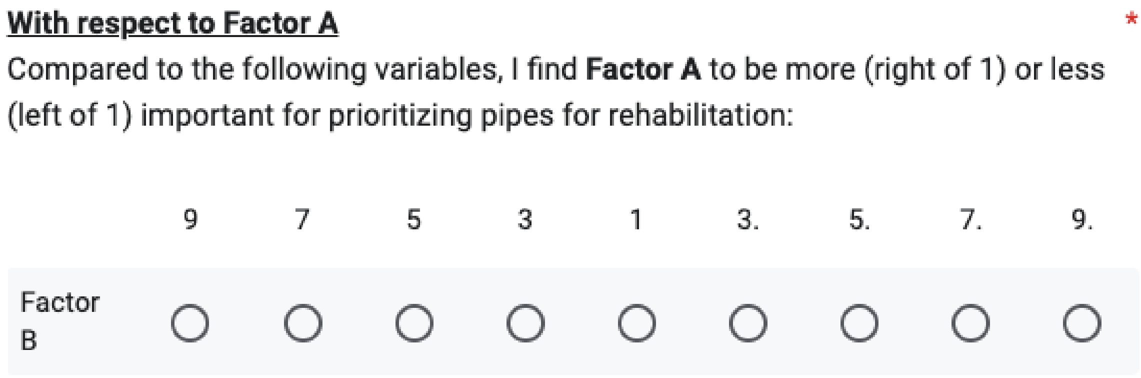


Figure 3.5: Example of the design of the questions in the questionnaire survey.

The pairwise comparisons were based on the scale of relative importance suggested by Saaty (1987), as shown in Table 3.4. The scale ranges from 1 to 9, where 1 indicates equal importance, and 9 indicates extreme importance. As seen from Figure 3.5, the intermediate values were excluded from the questionnaire to make it less complex and more understandable for the experts. In this questionnaire, seen in 3.5, if the selected value is on the left side of 1, then Factor B is judged to be more important than Factor A, which is mentioned at the top.

Table 3.4: Saaty's scale of relative importance used for pairwise comparisons (Saaty, 1987, p.163).

Numerical Value	Definition	Explanation
1	Equal importance	Factors a and b contribute equally to the objective.
3	Moderate importance	Slightly favour element a over b.
5	Strong importance	Strongly favour element a over b.
7	Very strong importance	Element a is favoured very strongly over b.
9	Extreme importance	Element a is favoured over b of the highest possible order of importance.
2, 4, 6, 8	Intermediate values	When compromise is needed. For example, 4 can be used for the intermediate value between 3 and 5.

Establishment of Pairwise Comparison Matrix

The pairwise comparison matrix was defined by Equation (3.1), where P is the pairwise comparison matrix, a_{ij} is the pairwise comparison between criteria i and j, and n is the number of criteria in the matrix (Thakkar, 2021, p.35). Further, $a_{ij} = 1$ for $i = j$ and $a_{ij} = 1/a_{ij}$ for $i \neq j$.

$$P = (a_{ij})_{n \times n} = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & 1 & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \tag{3.1}$$

First, the pairwise comparison matrix was normalised using Equation (3.2) (Hassoun Nedjar et al., 2023) to calculate the priority vector for each criterion. Here, r_{ij} is the normalised value of a_{ij}.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{3.2}$$

The priority vector was then determined by calculating the arithmetic mean of each row of the normalised matrix using Equation (3.3) (Hassoun Nedjar et al., 2023). Here, c_j is the average value of each row of the normalised pairwise comparison matrix, where r_{ij} is the normalised value and n is the number of criteria. The priority vector is also the relative weight of each criterion in the pairwise comparison matrix.

$$c_j = \frac{\sum_{i=1}^{n} r_{ij}}{n} \tag{3.3}$$

Consistency Analysis

When making pairwise comparisons, there will be inconsistencies in judgments due to human subjectivity. The judgments are considered consistent if the eigenvalue ($\lambda_{\max}$) of the pairwise comparison matrix is equal to the number of criteria (n) for expert-based comparisons (Thakkar, 2021, p. 35–36). Any difference between $\lambda_{\max}$ and the number of criteria indicates an inconsistency in the judgments (Thakkar, 2021, p. 35–36). The AHP method allows for some inconsistency, as some degree may be regarded favourably (Saaty, 2003; Saaty, 1987, p.86). To determine if the pairwise comparisons were consistent, the consistency ratio (CR) was calculated using Equation (3.4) for each pairwise comparison matrix(Abu Dabous & Alkass, 2008; Taherdoost, 2017, p.245). The CR value measures the consistency of the judgments made by the experts and was used to ensure that each matrix had an acceptable inconsistency rate.

$$CR = \frac{CI}{RI} \tag{3.4}$$

where CI is the consistency index, and RI is the random index. The CI value was calculated using Equation (3.5) (Hummel et al., 2014; Saaty, 1987, p.171). The RI

value is the average CI values from randomly generated pairwise comparison matrices and is independent of the matrix size (Saaty, 1987, p.171). In Table 3.5, the RI values are provided.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{3.5}$$

Here, $\lambda_{\max}$ is an approximation of the maximum eigenvalue, and n is the number of criteria. A close approximation to the maximum eigenvalue was calculated by multiplying the priority vectors with the pairwise comparison matrix (Thakkar, 2021, p. 38-39). First, the matrix product of the pairwise comparison matrix was determined by using Equation (3.6) (Thakkar, 2021, p. 38-39).

$$P \cdot C = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & 1 & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \cdot \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{3.6}$$

Here, P is the pairwise comparison matrix, and C is the corresponding priority vector. Then, the eigenvalue for each criterion was calculated following Equation (3.7).

$$\lambda_j = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \end{bmatrix} = \begin{bmatrix} y_1/c_1 \\ y_2/c_2 \\ \vdots \\ y_n/c_n \end{bmatrix} \tag{3.7}$$

Here, λ_j is the eigenvalue of j criterion, y_n is the matrix product of the pairwise comparison matrix and the priority vector, and c_n is the priority vector for each criterion. At last, the approximation to the maximum eigenvalue was determined by calculating the average of the eigenvalues using the following equation:

$$\lambda_{\max} = \frac{\sum_{i=1}^{n} \lambda_j}{n} \tag{3.8}$$

Here, $\lambda_{\max}$ is the maximum eigenvalue used in Equation (3.5) to find the consistency ratio, λ_j is the eigenvalue for the j criterion, and n is the number of criteria.

Table 3.5: Random index values for different matrix sizes (Saaty, 1980, as cited in Abu Dabous and Alkass, 2008, p.887).

Number of Criteria (n)	3	4	5	6	7	8	9	10	11	12	13
Random consistency (RI)	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.51	1.54	1.56

According to Saaty (1987), a CR value lower than 0.10 indicates an acceptable level of inconsistency. Otherwise, if the CR value is greater than 0.10, the pairwise comparisons should be revised so that the CR value does not exceed 0.10 (Thakkar, 2021, p.39). If the CR value is 0, it indicates that the pairwise comparisons are completely consistent (Thakkar, 2021, p. 36).

Aggregation of Pairwise Comparison Matrices

The final weights assigned to the criteria were calculated by aggregating each expert's pairwise comparison matrix as a geometric mean (Saaty, 1987, p.174) using Equation (3.9). Here, the pairwise comparison value (a_{ij}) from each pairwise comparison matrix was aggregated together into a new matrix.

$$w_{ij} = (a_{1j} \cdot a_{2j} \cdot a_{3j} \dots a_{nj})^{\frac{1}{n}} \tag{3.9}$$

where w_{ij} is the aggregated value of the a_{ij} value from each pairwise comparison matrix, and n is the number of criteria. Lastly, the priority vector was calculated for the aggregated matrix using Equation (3.3), to find the final group weight (Hummel et al., 2014).

3.3 Prioritisation with SAW

After determining the weights, the pipes were prioritised separately by the SAW method and TOPSIS method. Figure 3.6 illustrates the ranking process used in this thesis.

The decision matrix was defined by Equation (3.10), where A is the decision matrix with m criteria and n alternatives or pipes. Further, x_{ij} is the pipe data for each criterion.

$$A = (x_{ij})_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{ij} \end{bmatrix} \tag{3.10}$$

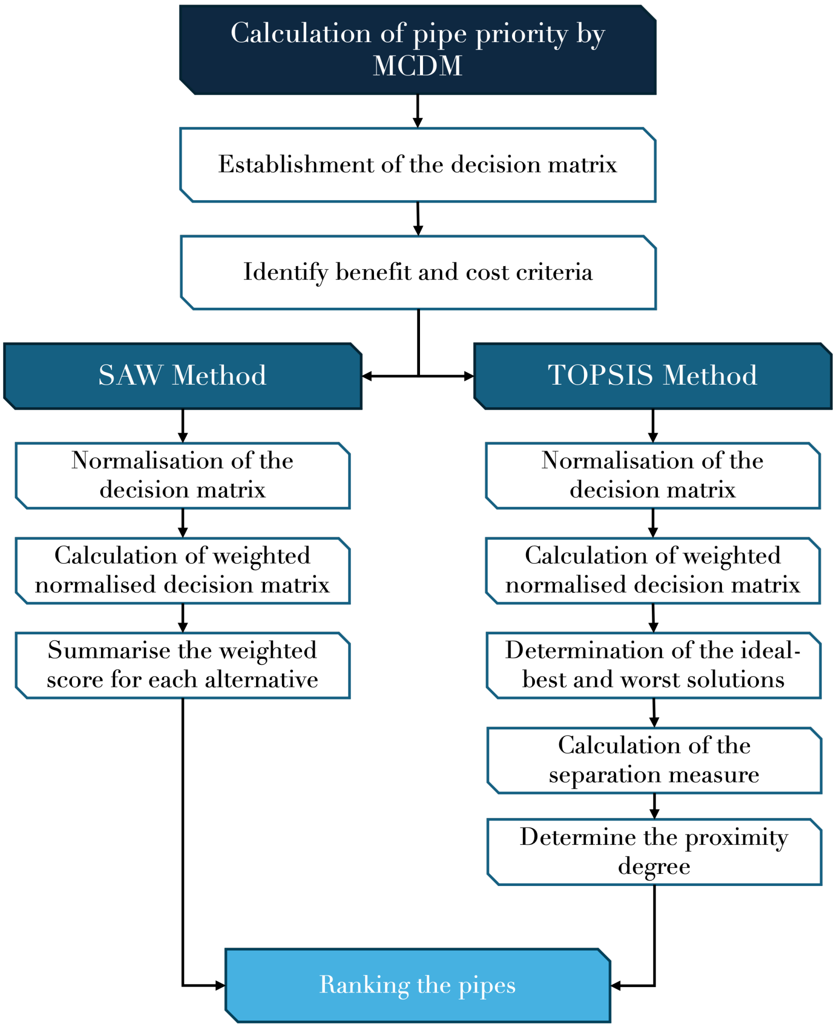


Figure 3.6: The flowchart for the ranking process with SAW and TOPSIS.

First, the decision matrix was normalised using the Max-Min normalising technique (Vafaei et al., 2022, p.1232). With Equation (3.11), the benefit criteria (r_{ij}^{+}) were normalised, and the cost criteria (r_{ij}^{-}) were normalised using Equation (3.12) (Vafaei et al., 2022, p.1232).

$$\text{Benefit Criterion: } r_{ij}^{+} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}} \tag{3.11}$$

$$\text{Cost Criterion: } r_{ij}^{-} = \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}} \tag{3.12}$$

where $x_{\min}$ is the minimum x_{ij} value in the column, $x_{\max}$ is the maximum x_{ij} value, and $r_{ij} \in [0, 1]$. The priority of each alternative was calculated by summing up the products of the normalised value of each alternative and the respective weights for each criterion, as shown in Equation (3.13) (Taherdoost, 2023, p.23).

$$S_i = \sum_{j=1}^{n} r_{ij} w_j \tag{3.13}$$

where S_i is the calculated score for each alternative, r_{ij} is the normalised value of each alternative, w_j is the weight of the j criterion and $\sum_{j=1}^{m} w_j = 1$.

Lastly, the alternatives, which in this thesis are the pipes, were ranked in descending order based on their scores, with higher scores indicating higher rehabilitation priority and lower scores indicating lower rehabilitation priority.

3.4 Prioritisation with TOPSIS

Unlike the SAW method, the TOPSIS method does not differentiate between benefit and cost criteria when normalising the decision matrix. Therefore, to standardise the scale for each factor, the decision matrix was normalised by the following Equation (Thakkar, 2021, p.83-85):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{3.14}$$

where r_{ij} is the normalised value of x_{ij}. The weighted normalised decision matrix was then obtained by multiplying the normalised values with the respective weights, as shown in Equation (3.15).

$$v_{ij} = r_{ij} w_j \tag{3.15}$$

Here, v_{ij} is the weighted normalised value of x_{ij}, r_{ij} is the normalised value, and w_j is the weight of the j criterion. Afterwards, the ideal-best solution and the ideal-worst solution were determined using the equations below:

$$A^+ = \{(\text{max} v_{ij} | j \in J), (\text{min} v_{ij} | j \in J')\} \tag{3.16}$$

$$A^- = \{(\text{min} v_{ij} | j \in J), (\text{max} v_{ij} | j \in J')\} \tag{3.17}$$

where A^+ is the ideal-best solution, A^- is the ideal-worst solution, and J and J' are related to the benefit and cost criteria. In this case, the ideal-best solution represents the pipe with the highest risk of failure, while the ideal-worst pipe has the lowest risk of failure.

Next, the separation measure for each alternative was calculated. The separation measure from the ideal-best solution is defined by Equation (3.18).

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \tag{3.18}$$

where S^+ is the Euclidean distance from the i alternative to the ideal-best solution, v_{ij} is the weighted normalised value, and v_j^+ is the ideal-best value of the j criterion. The separation measure from the ideal-worst solution is defined by Equation (3.19).

$$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{3.19}$$

where S^- is the Euclidean distance between the i alternative and the ideal-worst solution, v_{ij} is the weighted normalised value and v_j^- is the ideal-worst value of the j criterion.

Afterwards, the proximity degree to the ideal solution was determined by the following equation:

$$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+} \tag{3.20}$$

Lastly, the alternatives, which represent the pipes, are ranked in descending order of the C_i^+ value, with a higher C_i^+ value indicating higher priority and a lower C_i^+ value indicating lower priority. If $C_i^+ = 1$, the i alternative is the ideal-best, which in this case is the pipe with the highest risk of failure. Meanwhile, if $C_i^+ = 0$, the i alternative is the ideal-worst, indicating the pipe with the lowest risk of failure.

3.5 K-means Clustering Technique

Clustering is an unsupervised machine learning technique that groups data together according to their similarity, where each group is called a cluster (Ikotun et al., 2023, p.179). The data points in each cluster have a higher similarity to each other than to data points in other clusters (Banihabib et al., 2020, p.7). K-means is a clustering method that groups the data points based on their proximity to the data centre of the respective cluster (Banihabib et al., 2020, p.7). These centre values, called centroids, are randomly selected at first based on the number of clusters defined (Ikotun et al., 2023, p.185). Afterwards, the distance between each data point and the chosen cluster centroid is compared for each cluster, based on the Euclidean distance (Jain, 2010, p.654), presented in Equation (3.21) (Ikotun et al., 2023, p.185).

Given a dataset X with x_i data points, where $i = 1, 2...n$ and is d-dimensional, the K-means clustering aims to divide the n data points into k clusters (Jain, 2010, p. 653–654). The square error between the data point and the cluster centroid is defined as

$$J(c_k) = \sum_{x_i \in c_k} ||x_i - \mu_k||^2 \tag{3.21}$$

Here, $J(c_k)$ is the square error, $||x_i - \mu_k||^2$ is the Euclidean distance between x_i data points in cluster c_k and μ_k cluster centroid (Ikotun et al., 2023, p.185). After all the data points are assigned to a cluster, the centroid μ_k is recalculated as the mean value of the cluster (Banihabib et al., 2020, p.7), as shown in Equation (3.22).

$$\mu_k = \frac{1}{n} \sum_{x_i \in c_k} x_i \tag{3.22}$$

where n is the number of data points in cluster c_k, and x_i is the data points in cluster c_k. Based on Equations (3.21) and (3.22), the data points are assigned to the cluster with the shortest distance between the data point and the cluster centroid (Ikotun et al., 2023, p.185). This is done by minimising the sum of square errors for each cluster following Equation (3.23).

$$J(C) = \sum_{k=1}^{K} \sum_{x_i \in c_k} ||x_i - \mu_k||^2 \tag{3.23}$$

Here, $J(C)$ is the total sum of square errors for all clusters, K is all the clusters, x_i is the data points in cluster c_k, and μ_k is the centroid of the c_k cluster (Ikotun et al., 2023, p.185). The algorithm continually reassigns each data point to the cluster with the shortest distance to the centroid (Jain, 2010, p.654). It continues these steps until the assignments of points to clusters stabilise, and no longer change (Banihabib et al., 2020, p.7).

In this thesis, k clusters are the rehabilitation classes, and the data points are the scores obtained for each pipe using the SAW and TOPSIS method described in Section 3.3 and 3.4. The cluster ranges determined by K-means were further used to visualise the rehabilitation priority for the pipes in GIS. The script for the K-means algorithm was generated by the AI tool ChatGPT, which was implemented using R-Studio. The cluster ranges obtained were validated by a Python script using the K-means algorithm, also generated by ChatGPT. Furthermore, ChatGPT guided with navigating in GIS to visualise the results.

4. Results and Discussion

Since AHP, SAW, and TOPSIS do not require complex algorithms, all the MCDM techniques were implemented manually in Excel following the method in Chapter 3. The pipes in this case study were prioritised according to the risk of failure by implementing SAW and TOPSIS methods, as mentioned earlier. AHP was used to obtain the weights of the criteria.

4.1 Weights of Criteria

A total of 9 questionnaires responses were collected from the questionnaire survey distributed among experts. Of these, 67% of the respondents worked in academia, 22% were municipal engineers, and 11% were consultants, as seen from Figure 4.1. The participants had specialisations in infrastructure asset management, wastewater and stormwater transport systems, hydraulics, water transport systems, urban water systems, water and wastewater engineering, and water and environmental engineering. Of these participants, 78% had a PhD degree, and 22% had a master's degree.

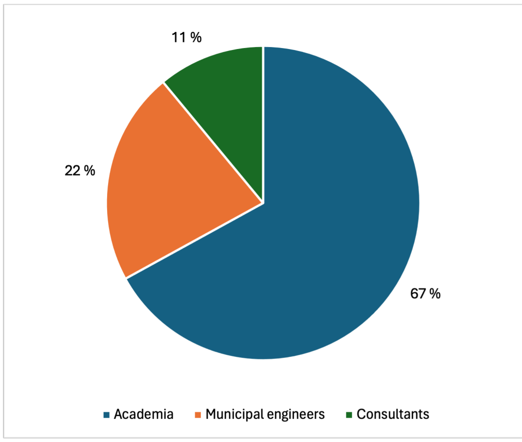


Figure 4.1: Distribution of the field of work of the experts who performed pairwise comparisons.

The CR values of all the pairwise comparisons were checked following the method presented in Section 3.2. Of the pairwise comparisons collected, only a few had a CR value lower than 0.10. However, most of the comparisons had CR values lower than 0.2. Thakkar (2021) stated that in some circumstances, CR values higher than 0.1 can be considered acceptable. Hummel et al. (2014) also suggested that a CR value lower than 0.1 is desired however, a CR value lower than 0.2 is tolerable. Therefore, in this thesis, the matrices with a CR value higher than 0.2 were discarded, and only those with a CR value lower than 0.2 were included in further calculations. As a result, only 7 out of the 9 respondents were included for further weight calculations. Ideally, the experts with inconsistent answers should have changed their answers to be more consistent. However, due to the time limitations and the amount of required pairwise comparisons, the experts were not asked to review and revise their responses. Consequently, the calculations were proceeded using the responses from the 7 experts who provided consistent answers. All the calculated CR values were verified using the Analytic Hierarchy Process Software 4.2.7 provided by Spice Logic. The CR value for the final aggregated comparison matrix, including all the pairwise comparisons of the consistent answers, was 0.02. Since the CR value for the aggregates pairwise comparison matrix was less than 0.1, these weights were accepted as the final weights.

Inspired by Tscheikner-Gratl et al. (2017), the standard deviation of the relative weights from each expert was calculated. As seen from Table 4.1, the standard deviation for the experts who were consistent in their judgments is lower than the standard deviation for all the experts. This indicates less variability and higher consistency in the judgments among the consistent experts, which further indicates less uncertainty. Furthermore, this can also be an indication that the experts had somewhat similar judgments when comparing the criteria with each other, as well as a similar understanding of the effect each criteria have on rehabilitation prioritisation. Tscheikner-Gratl et al. (2017, p.11–12) had a similar finding, noting that the standard deviation was higher for the judgement of all experts compared to only those with consistent judgments.

Upon a closer look at the standard deviation, the pipe renewal cost, Person Equivalent, and historical failure criteria have the highest standard deviation among the compared criteria. This suggests that there is less agreement among the experts on the importance of these criteria on the rehabilitation planning of wastewater collection networks compared to the other criteria. Especially, the standard deviation for historical failure among all experts is considerably higher than the rest of the criteria. However, since the standard deviations for the consistent experts are lower, the higher standard deviation for pipe renewal cost, Person Equivalent, and historical failure are not considered to be significant. The weights from the consistent comparisons were therefore determined as the final weights and used for further calculations.

The final weights for each criterion were calculated following the method in Section 3.2 is shown in Figure 4.2. As observed from the figure, the operational and economic factors are considered to have a higher influence on pipe rehabilitation than the physical and environmental factors. Historical failure has the highest influence on the rehabilitation planning of wastewater collection networks, with a weight of 24.5%. As discussed in Section 2.2.2, pipes with many historical failures often have poor conditions. Furthermore, failures often occur due to the influence of various other factors. Therefore,

Table 4.1: The standard deviation and overall weight for all the experts and the consistent experts.

	All experts		Consistent experts	
	Overall weight	**Standard deviation**	**Overall weight**	**Standard deviation**
Diameter	0.042	0.045	0.028	0.017
Pipe age	0.096	0.041	0.075	0.029
Length	0.033	0.028	0.029	0.020
Buried depth	0.048	0.024	0.040	0.022
Material quality	0.063	0.029	0.055	0.029
Slope	0.036	0.031	0.027	0.025
Maximum Velocity	0.030	0.017	0.025	0.013
Minimum Velocity	0.032	0.014	0.028	0.015
Pipe overload rate	0.111	0.041	0.117	0.041
Person Equivalents	0.067	0.041	0.066	0.046
Historical failure	0.191	0.075	0.245	0.044
Traffic load	0.087	0.031	0.090	0.032
Pipe renewal cost	0.164	0.059	0.174	0.054

historical failure is a good indicator of whether the pipe needs rehabilitation. The fact that historical failure is assigned the highest weight aligns with the literature. Since the municipality did not have available data regarding leakage and pipe bursts in this study area, historical failure is only represented by pipe blockages. In most cases, these blockages can be managed by maintenance, such as flushing the pipes, and do not always require rehabilitation. As a consequence, the pipes with blockages will be higher prioritised for rehabilitation in this study. This is discussed further in Section 4.4.

The weight of historical failure is followed by the pipe renewal cost and pipe overload rate, which weigh 17.39% and 11.69%, respectively. Cost is a huge factor that affects the decision making process when it comes to wastewater pipe management. The investment needs are funded by municipal housing charges, which also fund operational and maintenance costs related to the water and wastewater systems. Therefore, the budget allocated for managing wastewater collection networks is often very limited. The pipe overload rate indicates how often the pipe capacity has been exceeded, which can result in the flooding of manholes and building basements. The higher the pipe overload rate, the more exposed the pipe is to erosion. Therefore, the pipe overload rate will have a high influence on pipe degradation and rehabilitation.

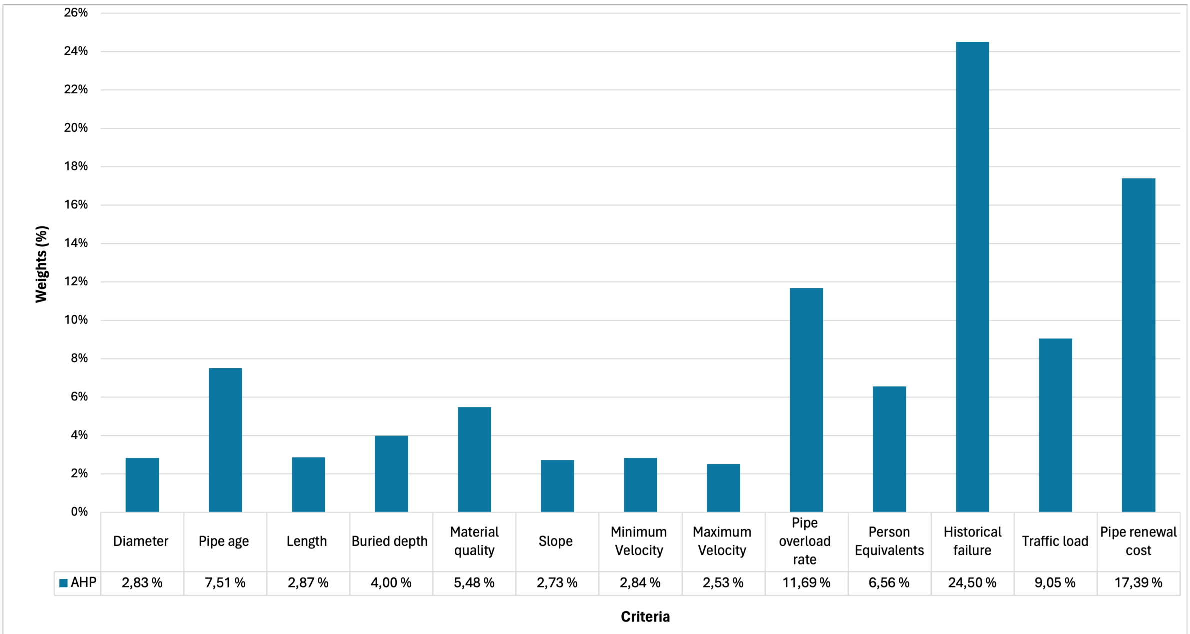


Figure 4.2: The final criteria weights are determined by the group AHP method. Here, the criteria are represented as the percentage of importance.

Meanwhile, the diameter, length, minimum velocity, maximum velocity, and slope are considered to have a much lower influence on rehabilitation planning, whereas the maximum velocity has the lowest influence, with a weight of 2.53%. As seen from Figure 4.2, these criteria have a similar influence on the prioritisation of rehabilitation for wastewater collection networks, considering the fact that their weights are very close to each other. The closeness in their weights indicates that these factors are important for analysing the wastewater collection networks. Physical factors alone cannot directly determine the condition of the pipes, but they can provide an indication as to which pipes are more susceptible to degradation. Among the physical factors, pipe age has the highest weight, followed by material quality. As mentioned in Section 2.2.1, pipe age often correlates with material quality and installation quality. Poor installation quality is often the main cause for pipe failure, as discussed in Section 2.2.1.

To summarise, it is apparent that historical failure and pipe renewal cost are the most important criteria, as they hold the highest weights, aligning with the literature discussed in Section 2.2. The diameter, slope, and velocities have weights that are comparable to each other, with the lowest weight influence.

Since these weights are defined by 7 experts, there are some subjective and uncertain aspects related to these weights. Uncertainties related to the interpretation of the criteria can influence the subjective weighting process. The reasoning behind the assigned weights for a criterion may differ from expert to expert, according to their perspective and understanding of the criteria. Therefore, it might be beneficial to combine the subjective weights with an objective weighting technique, such as Entropy or CRITIC, that can balance the subjectivity. Furthermore, due to the number of criteria defined in this thesis, 78 pairwise comparisons were required with the AHP method, which increases the complexity of the comparisons and is very time-consuming. Hence, the number of criteria should have been reduced by considering the most influential criteria for this specific study area while including the municipal workers in defining the criteria.

Moreover, as seen in Figure 4.1, the representation of municipal engineers is lower compared to other participants. Municipal engineers have more experience with the network in this study area. If the distribution of the participants was more equal, the criteria weights might have been more representative and somewhat varied. Therefore, in the future, the representability of the criteria weights might be enhanced by including the municipal engineers when defining and weighing the criteria. However, since the standard deviation for the judgment provided by the consistent experts is low, as discussed earlier, the criteria in this thesis are considered to be reliable.

4.2 Pipe Priority Analysis

After determining the weights with AHP, the pipe rehabilitation priority was determined using SAW and TOPSIS, following the method described in Section 3.3 and 3.4 . A sample of the decision matrix is provided in Table 4.2. The whole decision matrix is provided in Appendix B. All the matrices with calculations of SAW and TOPSIS, including the normalised decision matrices and weighted normalised decision matrices, are also provided in Appendix C and Appendix D.

4.2.1 Visualisation of the Results

To better understand the results in Appendix C and Appendix D, they were visualised using a GIS tool and the K-means clustering technique. For this purpose, the results from SAW and TOPSIS were divided into three priority levels, as shown in Table 4.3. Due to the small size of the study area and to make the results more easily interpretable for municipal workers, the group of clusters were limited to three. As seen from Table 4.3, the rehabilitation priority levels were divided into low, medium and high rehabilitation priority. Here, low rehabilitation priority is defined as pipes that have acceptable pipe conditions and have a low risk of pipe failure. Thus, these pipes do not need immediate rehabilitation efforts. Medium rehabilitation priority is defined as pipes with a moderate pipe failure risk. These pipes should be monitored and scheduled for inspection to assess the pipe condition. If these pipes are not maintained properly, their pipe condition will worsen, and eventually move priority levels to the high rehabilitation priority. Pipes with high rehabilitation priority are defined as pipes with a high risk of pipe failure

Table 4.2: Sample of the decision matrix used for SAW and TOPSIS calculations.

Pipe ID	Diameter [mm]	Pipe age [year]	Length [m]	Buried depth [m]	Material quality	Slope [%]	Minimum Velocity [m/s]	Maximum Velocity [m/s]	Pipe overload rate [%]	PE	Historical failure	Traffic load	Pipe renewal cost [NOK]
20097	230	66	61.4	2.5	Low	2.3	0.0095	0.4930	0	48	0	Medium	1,535,550
20234	200	50	40.5	2.5	Low	0.0	0.0000	0.0000	0	42	0	Low	1,011,275
20246	130	32	15.8	2.4	Very high	8.2	0.0562	1.1615	0	23	1	Low	395,000
20247	230	32	27.3	2.4	Very high	6.8	0.0557	0.9639	0	23	1	Low	682,975
20682	200	12	50.7	3.6	Low	0.6	0.0010	0.1381	100	115	0	Very low	1,267,550
22256	160	13	47.1	2.6	High	0.5	0.0049	0.2316	0	33	0	Low	1,176,825
22320	250	46	44.6	2.5	Low	1.0	0.3029	1.3419	0	241	0	High	1,337,160
22666	200	51	38.0	2.5	Low	23.9	0.0126	0.7618	0	304	0	Low	950,075
22668	200	51	53.9	2.5	Low	4.2	0.0126	0.5746	0	142	0	Low	1,348,125
92698	150	18	57.6	2.3	High	0.9	0.0116	0.5395	21.7	73	1	Low	1,439,400

and need immediate inspection to confirm the pipe condition. These pipes should be scheduled for pipe repair or replacement. The boundaries for each priority level were determined using the K-means clustering algorithm in R-studio. Afterwards, the results were visualised in a GIS tool according to the priority levels defined in Table 4.3, and the ranges obtained from K-means clustering.

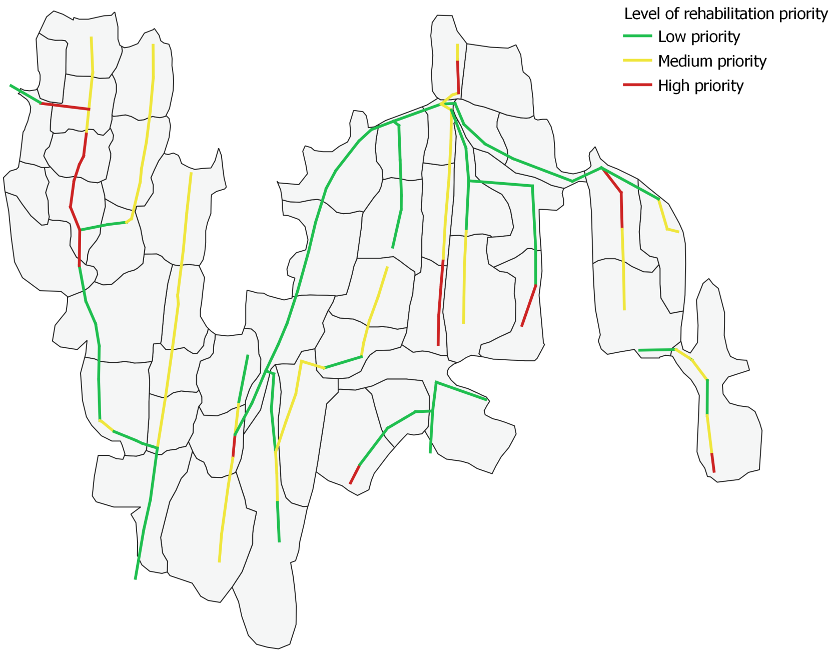
Table 4.3: The rehabilitation priority levels and their definitions.

Cluster	Rehabilitation priority level	Definition
1	Low priority	The pipe has low risk of failure. No immediate action is needed.
2	Medium priority	The pipe has medium risk of failure. The pipes should be schedueld for inspection and maintainance.
3	High priority	The risk of pipe failure is high. The pipe must be prioritised for immediate inspection and rehabilitation activities should be planned.

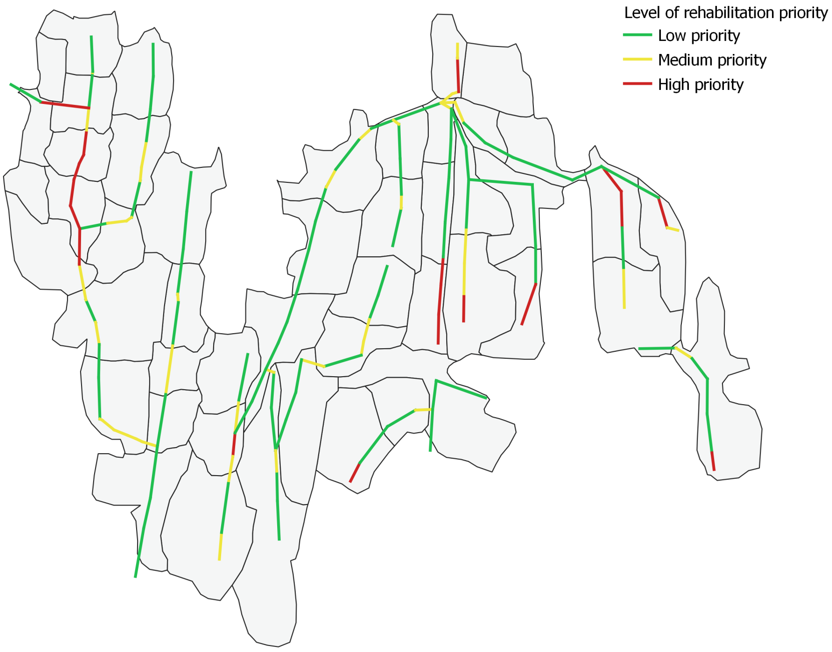
Figure 4.3 visualises the results of rehabilitation prioritisation calculated with the SAW and TOPSIS techniques. According to SAW, as seen in Figure 4.3a, the western and the southeast parts of the study area have the most pipes with high and medium rehabilitation priority. The length of the pipes categorised as high priority for rehabilitation is 767.2m, constituting 12% of the total pipe length in the study area. All the pipes that had historical failure are included in the high rehabilitation priority category. This is due to historical failure having the highest weight of all criteria. The rough cost estimation used to calculate the renewal cost of each pipe estimates the total cost for rehabilitation of the high-priority pipes at 19 372 000 NOK.

Similarly, according to TOPSIS, as seen in Figure 4.3b, the pipes identified to have high rehabilitation are mostly the same as SAW. The pipe length of the pipes classified as high-priority pipes is 857.6m, which equals 13% of the total pipe length in the study area. The cost estimated for renewing these pipes with the TOPSIS method is 21 632 000 NOK. Moreover, TOPSIS classifies more pipes as low rehabilitation priority compared to SAW.

Figure 4.3 shows that the results from SAW and TOPSIS are similar. The main difference is that TOPSIS has more pipes classified as low priority than the SAW method. The few pipes classified as high-priority pipes with TOPSIS but not with SAW have been categorised as medium-priority pipes with the SAW method. Similarly, some of the pipes classified as low-priority pipes with TOPSIS are classified as medium-priority pipes using the SAW method. This suggests that SAW identifies more pipes for rehabilitation and maintenance than TOPSIS does. Figure 4.4 further underscores this point, showing the percentage of the pipes classified as high, medium, and low priority in terms of the pipe length. For SAW, 47.5% of the total pipe length is categorised as high or medium priority. On the other hand, only 31% of the total pipe length is categorised



(a) SAW



(b) TOPSIS

Figure 4.3: Results of wastewater collection pipe prioritisation using the SAW and TOPSIS method in combination with the AHP weighting method.

as high or medium priority with TOPSIS. Moreover, from Figure 4.4, it is also clear that the distribution of pipes classified as high priority is approximately equal for both SAW and TOPSIS. The main difference is that TOPSIS has more pipes classified as low priority than the SAW method. Consequently, TOPSIS has fewer pipes in the medium rehabilitation priority group. This can also be seen in Table 4.4. Therefore, TOPSIS can be considered a more optimistic method than SAW, possibly underestimating the urgency of pipe maintenance needs compared to SAW. The medium-priority pipes are equally as important as the pipes in the high rehabilitation priority group. If these pipes are not properly maintained, they could quickly escalate to the high-priority group.

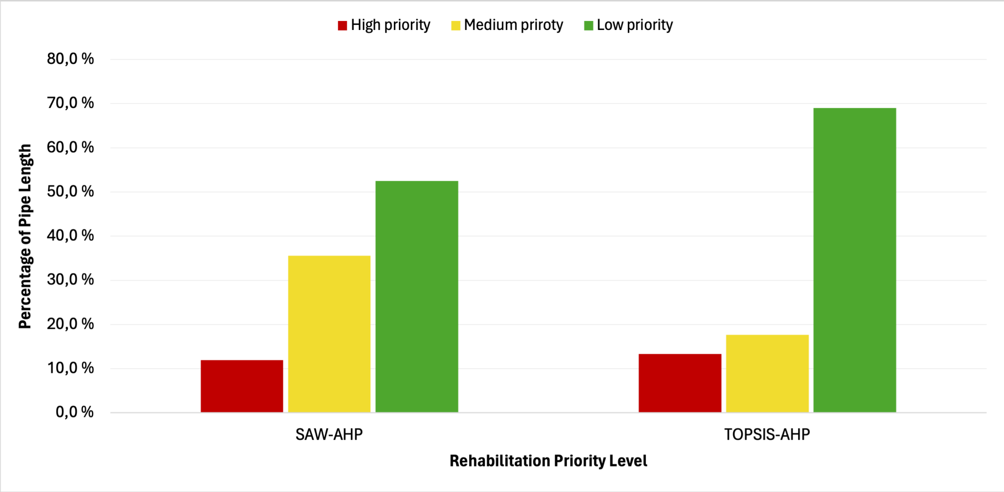


Figure 4.4: The percentage of the pipes categorised as high, medium and low rehabilitation priority in terms of the pipe length.

Table 4.4: The number of pipes and the length of pipes categorised as high, medium and low rehabilitation priority levels for SAW and TOPSIS, with the respective cluster ranges.

		SAW		**TOPSIS**	
High priority	Number of pipes (%)	17	(13%)	19	(14%)
	Total pipe length [m] (%)	767.3	(12%)	857.6	(13%)
	Cluster range	0.18 – 0.33		0.13 – 0.22	
Medium priority	Number of pipes (%)	54	(40%)	45	(33%)
	Total pipe length [m] (%)	2290.6	(36%)	1137.0	(18%)
	Cluster range	0.33 – 0.46		0.22 – 0.32	
Low priority	Number of pipes (%)	64	(47%)	71	(53%)
	Total pipe length [m] (%)	3379.1	(52%)	4442.4	(69%)
	Cluster range	0.46 – 0.74		0.32 – 0.72	

One of the reasons TOPSIS is more optimistic may be because of its ranking method. TOPSIS is a distance-based method that ranks the alternatives based on their proximity to the ideal-best solution, while also considering the distance from the ideal-worst solution. On the other hand, SAW ranks the alternatives solely based on the weights assigned to the criteria and does not take ideal solutions into account. Since TOPSIS aims to find alternatives that are closer to the ideal-best solution, it could result in more optimistic results.

In Figure 4.5, the distribution of the pipe material in each category with the SAW and TOPSIS method is visualised in terms of pipe length. As the figure shows, most of the concrete pipes are classified as high- or medium-priority pipes with SAW, while PVC and HDPE pipes are mainly categorised as low-priority. Furthermore, with SAW, medium-priority pipes have the highest rate of concrete pipes compared to the other two categories. However, with the TOPSIS method, the distribution of pipe material is more even throughout each category, as seen in Figure 4.5. Here, none of the categories has a highly dominating pipe material. Additionally, due to the history of pipe materials in Norway, where older pipes were made of concrete and newer pipes are made of plastic, Figure 4.5 indicates that TOPSIS also have a more even distribution of pipe age compared to SAW. This could again indicate that SAW, identifies more pipes in the medium rehabilitation priority group, giving more importance to the medium-priority pipes needing maintenance than TOPSIS does. The reason TOPSIS results in a more even distribution of pipe materials is likely due to the difference in SAW and TOPSIS ranking mechanisms. In addition, material quality had a moderate weight in comparison to the other criteria, which could contribute to the distribution of material in the different categories.

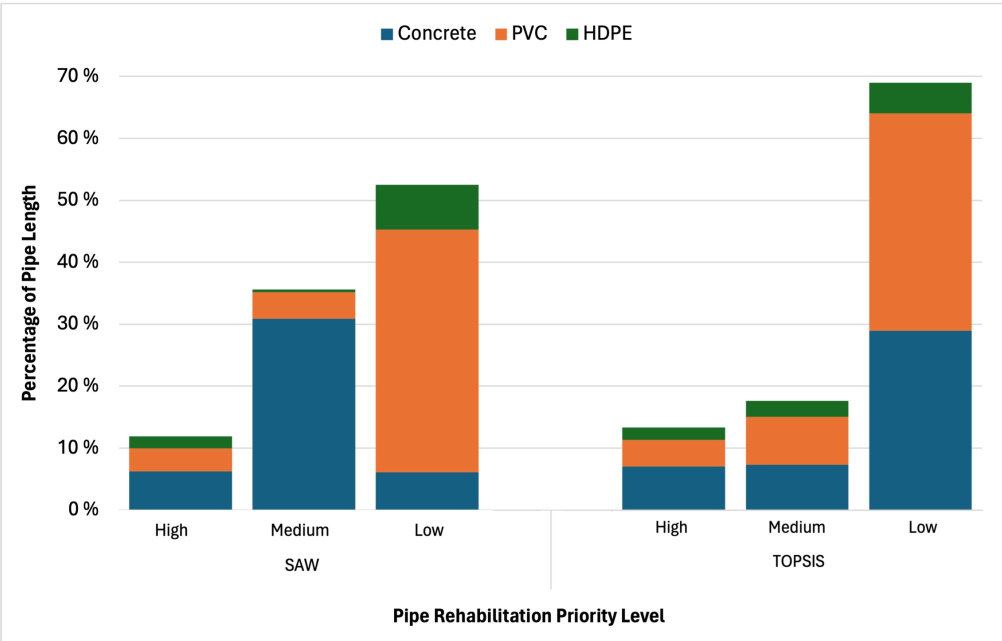


Figure 4.5: The distribution of pipe materials in terms of pipe length for high-, medium-, and low-priority pipes for SAW and TOPSIS results.

Nordre Follo municipality had a rehabilitation rate of 0.5% in 2023 (R. M., Aamodt, personal communication, April 2024). When comparing this to the pipe length that requires rehabilitation, it is clear that Nordre Follo does not have a sufficient rehabilitation rate to match the need for rehabilitation. Furthermore, this rehabilitation rate is also below the renewal rate recommended by Norwegian Water for wastewater collection networks at 0.88%. The rehabilitation needed for this particular study area is approximately 11.9% with the SAW method and 13.3% with the TOPSIS method. If only the pipes constructed before 2000 are considered, the need for rehabilitation would be approximately 9.0% with the SAW method and 9.8% with TOPSIS. On the other hand, if the pipes categorised as medium priority are included in the rehabilitation rate, as rehabilitation and maintenance, the difference between the rehabilitation rate and the rehabilitation need is even more significant. With the SAW method, rehabilitation and maintenance needs amount to 47.5%, while the TOPSIS method amounts to 31%. This indicates that the rate at which the municipality rehabilitates the pipes is considerably lower than the rehabilitation needs. Based on these results, the rehabilitation rate must be sufficient to meet the rehabilitation need at 9% in order to replace the oldest pipes in the network, at a minimum. Additionally, the calculated rehabilitation rate needed only considers pipe failures due to blockages. Meanwhile, the municipality's rehabilitation rate may include other pipe failures, such as leakage and pipe bursts.

However, it must be noted that the rehabilitation rate of 0.5% is the annual rate of rehabilitation and applies to the municipality's entire wastewater collection network, which includes Ski, Oppegård, and Kolbotn, among other areas. This case study is only a small part of the whole network in Kolbotn. If the MCDM techniques were applied to the whole wastewater collection network of Kolbotn, the rehabilitation needs might be even more representative. Also, it is not given that all pipes classified as high priority need to be replaced immediately, but they should be considered for rehabilitation before the other pipes in the other categories. Therefore, the rate of rehabilitation needed in this study represents the total amount of rehabilitation needed for this area. It will take a few years to rehabilitate and maintain all these pipes. Hence, the rehabilitation need cannot be directly compared with the municipality's rehabilitation rate but can, to some extent, be provided as an indicator. Overall, Nordre Follo municipality is advised to increase its rehabilitation and maintenance activities.

4.3 Analysis of Pipes with High-Priority

A thorough examination of the pipes classified as high-priority is necessary for a better understanding. Table 4.5 presents the number of pipes with historical failures and a pipe overload rate of 100% among the pipes categorised as high rehabilitation priority. From the table, it is clear that both SAW and TOPSIS have classified all the pipes with historical failures as high-priority pipes. SAW had 17 pipes in the high rehabilitation priority category, all of which were pipes with historical failures. These 17 pipes were the only ones that had historical failure among all the pipes evaluated in this thesis. Only 1 pipe with a 100% pipe overload rate was detected among the high-priority pipes, which was a pipe that also had historical failure. TOPSIS also had 17 pipes with historical failure of the pipes classified as high-priority pipes, in addition to 2 more pipes that had a pipe overload rate of 100%. Since TOPSIS classified 19 pipes as high-priority pipes, the percentage of pipes with historical failure among these pipes is lower for TOPSIS compared to SAW. However, they have the same amount of pipes with historical failure. Both of the MCDM techniques in this study have successfully identified all the pipes with historical failure as pipes with high rehabilitation priority.

Table 4.5: The number of pipes and the percentage of pipes with historical failure and a pipe overload rate of 100% of the pipes categorised as high rehabilitation priority for SAW and TOPSIS.

	SAW		**TOPSIS**	
	Number of Pipes	Percentage of Pipes	Number of Pipes	Percentage of Pipes
Historical failure	17	100%	17	89%
100% pipe overload rate	1	6%	3	16%

As observed in Figure 4.6, both SAW and TOPSIS have a similar distribution of pipe material in terms of pipe length for the pipes classified as high rehabilitation priority. Moreover, for both methods, concrete accounts for more than 50% of the pipes classified as high-priority in terms of pipe length. As discussed in Section 2.2.1, concrete pipes are usually affected more by chemical degradation due to the development of H_2S gas in the pipes. In addition, the concrete pipes constructed between 1945 and 1970 are known to have low installation quality and generally have poor pipe conditions. Therefore, concrete pipes were categorised as low material quality. Following concrete, PVC and HDPE pipes account for approximately 30% and 15% of the pipes in the high rehabilitation priority, respectively.

The average pipe age for the pipes categorised as high-priority with SAW is 39,1 years, while for TOPSIS, it is 36,3 years. For SAW, as seen from Figure 4.7a, 76% of the number of high-priority pipes were constructed before 1992. Similarly, 68% of the num-

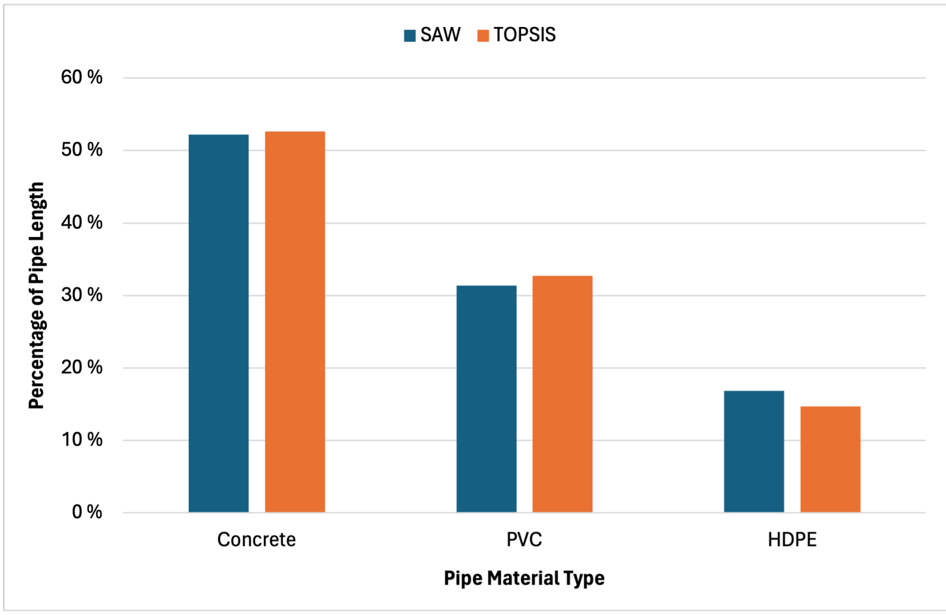
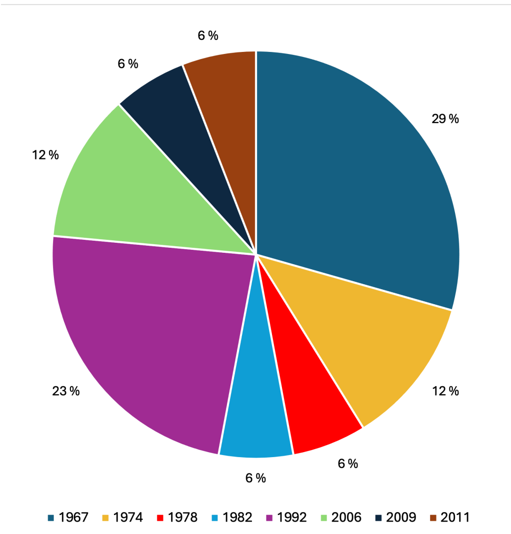
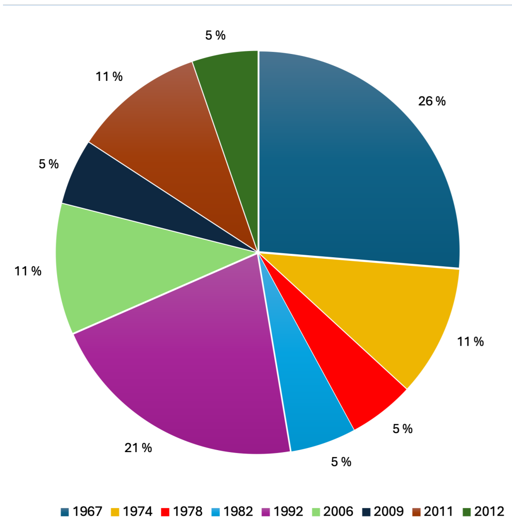


Figure 4.6: The distribution of pipe materials for the pipes classified as high rehabilitation priority in terms of pipe length.

ber of pipes are older than 1992 with the TOPSIS method, as seen in Figure 4.7b. For both SAW and TOPSIS, most of the pipes with high rehabilitation priority are pipes constructed in 1967, closely followed by pipes from 1992. This suggests that in this particular study area, pipes older than 1992 are likely to be in poor condition. Upon closer analysis, it is clear that the newer pipes in this category are pipes with historical failure or a 100% pipe overload rate. This applies to both SAW and TOPSIS. As previously mentioned, the historical failure criteria received the highest weight. Therefore, some newer pipes with historical failure were also classified as high rehabilitation priority.



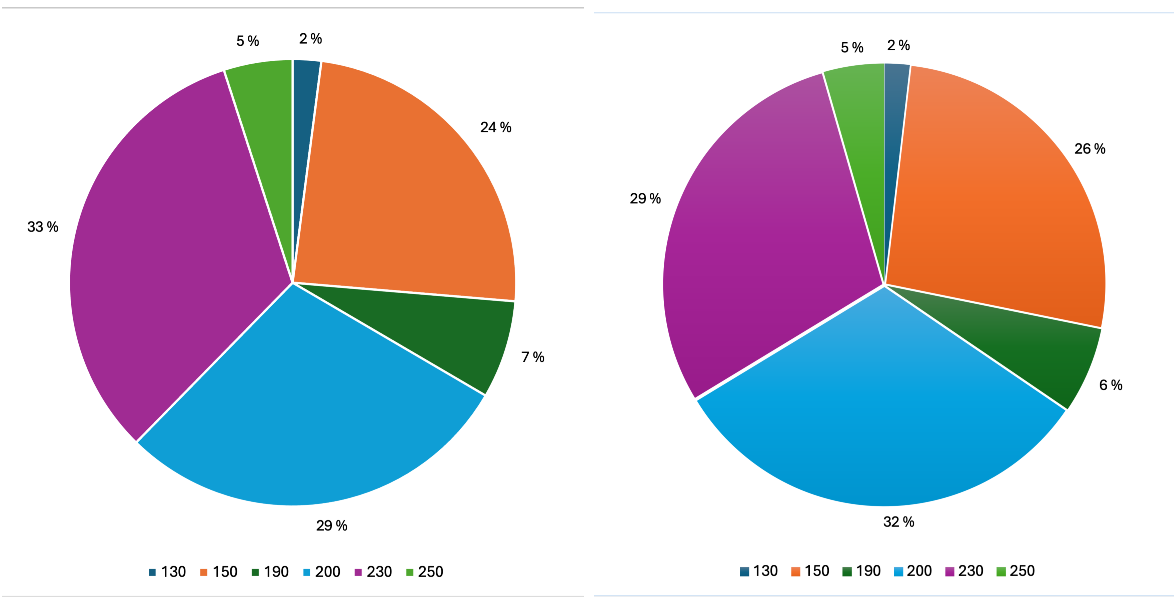
(a) SAW



(b) TOPSIS

Figure 4.7: The construction year for the pipes that are categorised as high rehabilitation priority in terms of number of pipes.

In Figure 4.8, the range of the pipe diameters for the high-priority pipes with SAW and TOPSIS are presented. As seen in the figure, the distribution of pipe diameters is reasonably even between the diameters 150, 200, and 230mm. For SAW and TOPSIS, most of the pipes are 230mm pipes, half of which are concrete pipes, and the rest are HDPE pipes. The difference in the distribution of pipe diameter equal to 150 or 200 mm is minimal for both methods. With SAW, more 200mm pipes are categorised as high-priority than 150mm pipes. Meanwhile, for TOPSIS, it is the opposite. The reason for pipes with higher diameters being categorised as high rehabilitation priority is most likely because 66% of the pipes in the study area have either 150, 200, or 230 mm diameter. In addition, the pipe diameter had one of the lower weights compared to all criteria. Upon closer analysis of the concrete pipes constructed before 1992, it is clear that the most common diameters are 200mm and 230mm pipes, which account for 37% of all the pipes in the high-priority category.



(a) SAW **(b)** TOPSIS

Figure 4.8: The range of pipe diameter for the pipes classified as high-priority in terms of pipe length.

In summary, the distribution of pipe material, diameter, and age for the pipes categorised as high rehabilitation priority is similar using both SAW and TOPSIS methods. The majority of these pipes are 200mm or 230mm concrete pipes constructed before 1992. This aligns with the literature stating that concrete pipes installed between 1945 and 1970 are usually of poor quality. Furthermore, this suggests that the concrete pipes installed between 1967 and 1992, which were not classified as high priority, should be examined further. This recommendation is particularly relevant for this study area, as these pipes seem more likely to be in poor condition. Additionally, due to the weight of the historical failure criteria, some newer pipes were also classified into this category.

The analysis further reveals that all the pipes classified as high-priority have a historical failure rate, a 100% pipe overload rate, or both.

4.4 Uncertainties and Limitations

In this thesis study, the uncertainties are mainly connected to the data used for conducting this rehabilitation assessment. As mentioned in Section 3.1.2, the velocities and pipe overload data are simulated values from Nordre Follo Municipality's MIKE URBAN model. The precipitation data for the simulation was from Oslo instead of precipitation data for Kolbotn, which was supposedly larger. Additionally, the simulation was run without taking evaporation into consideration. Hence, the water volume used for simulation is excessive, resulting in high pipe fillings and increased maximum velocities. However, the relative differences should be fairly consistent since the water is evenly distributed throughout the network. Therefore, this is not regarded as a significant uncertainty.

Some of the criteria defined in this thesis are dependent on each other. For instance, pipe overload mainly depends on the pipe slope and wastewater load, as well as minimum and maximum velocities depending on the pipe slope. These dependencies between the criteria were not determined when the weights were assigned to them, and they could have influenced the results. As a consequence, these criteria may have received higher weights than they should have, favouring them over the other criteria. On the other hand, these dependencies can increase the complexity of the pairwise comparison with AHP. This can make it difficult for the experts to distinguish between these dependent criteria. This could further increase the potential for inconsistent comparisons and be a reason for the inconsistencies in some pairwise comparisons. By considering dependent criteria, the number of criteria could have been reduced, leading to fewer pairwise comparisons and less uncertainty in the results.

The pipe renewal cost in this thesis was based on cost estimations provided by Nordre Follo municipality, which were applied for each pipe based on the pipe length. In other words, the cost criterion is dependent on the pipe length and has been given more importance, even though the criterion pipe length received a lower weight. Due to the high weight of the cost criterion, pipes with higher renewal costs were given lower prioritisation than the shorter ones. Accordingly, the longer pipes were considered to have low rehabilitation priority despite being older concrete pipes. Figure 4.9 illustrates the pipe length distribution in the different categories using the TOPSIS method. From the figure, one can see that the longer pipes are mainly classified as low priority. This also applies to pipe length distribution using the SAW method. Consequently, the cost criterion leads to the focus on minimising costs rather than maximising efficiency. In addition, the high weight assigned to the pipe renewal cost could lead to pipes being rehabilitated earlier than needed, wasting time and resources while overlooking the pipe condition. Therefore, assigning a high weight to pipe renewal cost rather than other factors influencing the pipe condition directly is not a sustainable approach for the long-term management and maintenance of the wastewater collection network. To optimise this method, it is therefore recommended to identify the dependent criteria, and either combine them or use an MCDM method that considers the criteria that are dependent on each other.

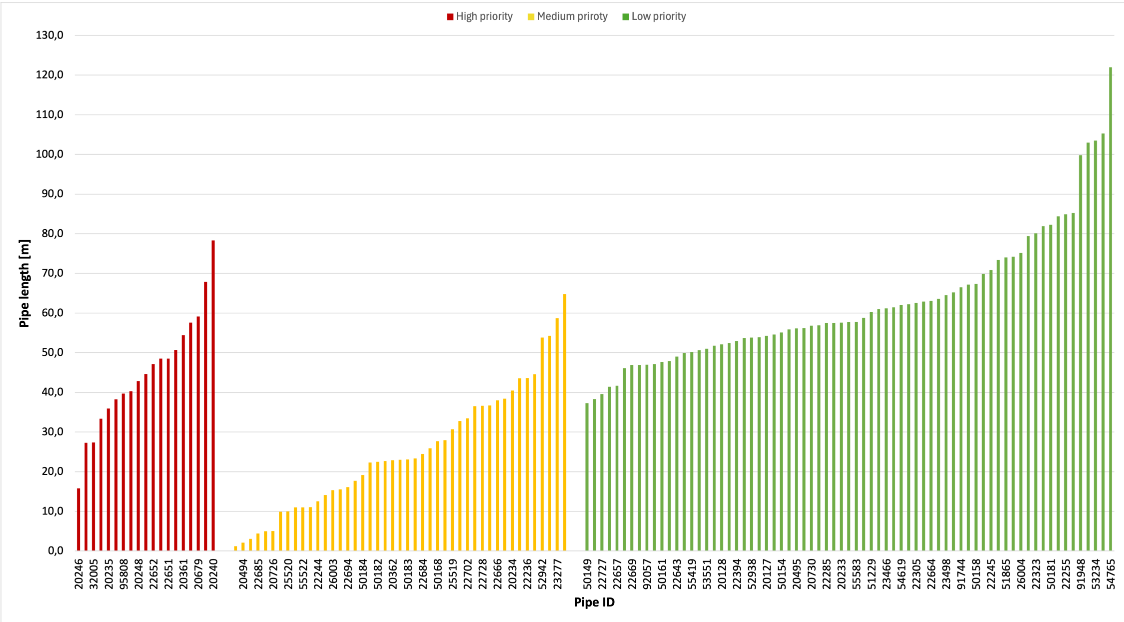


Figure 4.9: The distribution of pipe length in meters in the different categories with the TOPSIS method. Here, the red ones are pipes categorised as high priority, yellow is medium priority, and green is low priority pipes.

As previously discussed, the historical failure data available for the study area only consisted of pipe blockages. Therefore, this study did not represent other forms of failure, such as leakage or pipe burst. Due to a lack of available data and poor data quality regarding historical failure, these other forms of failure were not included. Due to historical failure receiving the highest weight, the importance of blockages may have been overly emphasised. Blockages occur due to sedimentation, biofilm growth, or the accumulation of grease and fat, and can often be fixed by flushing the pipes with high-pressure water jets. Blockages are considered an operational pipe failure and are usually signs of poor pipe condition. In the worst case, blockages can lead to potential bursts. Nevertheless, the historical failure criterion was defined as the number of failures due to blockage, leakage or breakage and not as the number of times blockages did occur. As seen from the results, this led to a few of the newer PVC pipes being classified as high rehabilitation priority when there might be other older concrete pipes in worse conditions. For this reason, the definition of the high rehabilitation priority category is therefore changed to pipes that should be scheduled for rehabilitation and maintenance activities.

Like many other municipalities in Norway, one of the main issues that Nordre Follo municipality encounters is a high leakage rate. Unfortunately, leakage data was not available for this study area and therefore not included in the assessment. As a result, the pipes with high leakage rates were not identified or considered as problematic pipes. This is considered a significant limitation. Therefore, this method is not representative as a rehabilitation assessment technique for Nordre Follo municipality. However, this method is still representable for assessing rehabilitation and maintenance for this study area. For a more accurate representation of the municipality's leakage problems, it would have been beneficial to incorporate the leakage rate of each pipe into the assessment. This underscores the importance of having available data with representational quality for a more accurate assessment of the municipalities' wastewater collection networks.

As seen from the results in Section 4.2, especially with SAW, few concrete pipes were identified as needing rehabilitation. Concrete pipes are highly exposed to chemical degradation and can corrode both internally due to H_2S gas and externally due to corrosive environments. This study did not include soil type and groundwater level as criteria because of the lack of available data. As a result, the potential risk of failure for concrete pipes is not fully represented, and the number of concrete pipes in poor conditions may have been underestimated. If these criteria were considered with appropriate weights, more concrete pipes could have been classified as high priority. In the future, including these criteria in the MCDM study could be valuable to enhance the accuracy of pipe rehabilitation priority assessments.

Due to the limitation of negative values in SAW and TOPSIS, these values were set to zero when preparing the decision matrix. This specifically applies to the negative values for the pipe slope. Therefore, the negative values were values were distinguished from the rest of the data. Although the slope criterion had a lower weight, the transformation of negative values to zero could still introduce uncertainty into the prioritisation. A consequence of changing the data is overlooking potentially meaningful variations in the dataset. This uncertainty could have been reduced if the negative values had been transformed by adding a constant to make them positive. This approach would have maintained differentiation between data, allowing the full range of values to be considered in the MCDM analysis instead of neglecting the negative values.

4.4.1 Validation

Validating the results is important to ensure their reliability and address the uncertainties discussed in Section 4.4. To approve the pipes classified into high, medium, and low rehabilitation priority using the SAW and TOPSIS methods, the pipes in the low-priority category were analysed to determine if there were any historical failures or pipe overload rates. As mentioned earlier, no pipes with historical failures or high pipe overload rates were found among the pipes classified as low-priority for both SAW and TOPSIS. Nonetheless, with the SAW method, some pipes with lower overload rates were detected among the low-priority pipes. Also, pipes with high pipe overload rates were detected in the medium-priority group. For the TOPSIS method, only pipes with an overload rate of 3.1% were identified among low-priority pipes and none among the medium-priority pipes. This further indicates that both SAW and TOPSIS results align with the criteria weighting. It is important to note that the TOPSIS method is a little optimistic when classifying the low-priority pipes, as discussed earlier. With a closer look at the pipes classified as high-priority, it is evident that the pipes in this rehabilitation priority category with the SAW method are exactly the same as those identified as high-priority with the TOPSIS method. The only difference is that TOPSIS has two more pipes in this category than SAW. Based on this, the pipe classification results were approved.

For validation, the results were cross-checked with measurements of *Escherichia coli* (*E. coli)*, which is a natural component of wastewater. These measurements are conducted in streams or stormwater manholes, and the detection of *E.coli* either indicates leakage or overflow (R.M., Aamodt, personal communication, April 2024). The measurements shown in Figure 4.10, are measurements from a dry period in 2023 and indicate leakages from pipes in the area. According to Nordre Follo municipality, an *E.coli* concentration above 1000 *E.coli*/100mL water is considered as leaking pipes (R.M., Aamodt, personal communication, April 2024). The *E.coli* measurements were only conducted for the lower part of the wastewater collection network, which is unfortunately not a part of this particular study area. Therefore, in this thesis, there is no data to validate the results from the SAW and TOPSIS methods. In spite of this, comparing Figure 4.10 and Figure 4.3, the few pipes that are a part of the case study and have an indication of leakage, are either considered as medium or high-priority pipes. This suggests that the criteria included in this thesis can also be factors influencing leakage. However, if the leakage data had been available for the study area as well, the pipe prioritisation with SAW and TOPSIS would have been more representative and reliable for this study area.

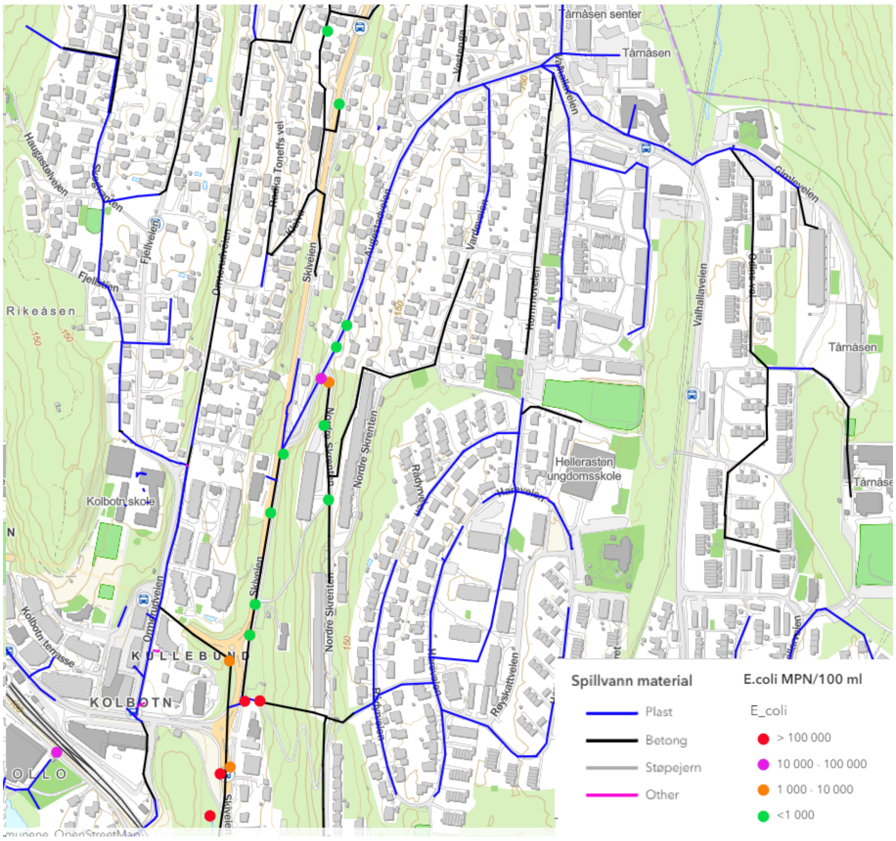


Figure 4.10: Measurement of E.coli from a dry period in 2023, which indicates leakages from pipes in the area. The blue lines are plastic pipes, and the black are concrete.

Since the results from the MCDM techniques could not be validated through actual inspection data and other measurements to indicate the pipe condition, the results were sent to Nordre Follo municipality for validation. They confirmed that the results were reasonable and that they made sense with their predictions. Nordre Follo municipality noted that the SAW results were more accurate than the TOPSIS results, due to SAW categorising more pipes in the southern area as high- or medium-priority pipes (R.M., Aamodt, personal communication, April 2024). They justified this based on known leakage problems in this area caused by old concrete pipes. This validation from the municipality is used as a confirmation of these results.

Due to time limitations, a sensitivity analysis was not conducted. A sensitivity analysis is used to check the robustness of the MCDM result for changes in the criteria (Thakkar, 2021, p.24). Furthermore, a sensitivity analysis can help identify the criteria with the highest impact on the results. Therefore, for future works it is recommended to supply the results with a sensitivity analysis to further validate the MCDM results.

5. Conclusion

This thesis presented the application of the MCDM techniques, specifically SAW and TOPSIS, for planning rehabilitation for wastewater collection networks with a focus on pipe prioritisation. These techniques were implemented in a case study, which is a small part of Kolbotn in Nordre Follo municipality, Norway. For this purpose, 13 criteria, including physical, operational, and environmental pipe deterioration factors, were considered, along with pipe renewal cost. These criteria were weighted using the group AHP method based on the judgments from 7 experts. The pipes were then evaluated according to the criteria weights, and the final results were categorised into three rehabilitation priority groups using the K-means clustering technique and GIS. The following findings were made in this thesis study:

- According to the experts' judgements, historical failure and pipe renewal cost received the highest weights with the AHP method. These criteria had a large influence on the results. The diameter, slope, and velocities received the lowest weight influence, and their weights were similar.
- While both SAW and TOPSIS methods identified similar pipes as having high rehabilitation priority, there is a noticeable difference in the categorisation of pipes with low- and medium rehabilitation priority. TOPSIS was more optimistic when categorising pipes with low rehabilitation priority, consequently having fewer pipes in the medium priority category. This suggests that TOPSIS may be underestimating the maintenance needs of the pipes.
- Generally, TOPSIS had a more even distribution of pipe materials among the rehabilitation priority levels than SAW. With SAW, most of the concrete pipes were categorised as either high- or medium-priority. This again indicates that SAW identifies more pipes in the medium rehabilitation priority group than TOPSIS does.
- The pipes in the high rehabilitation category are mainly concrete pipes with diameters of 200mm or 230mm, constructed between 1965 and 1992 for both MCDM methods. All of these pipes had historical failures, a pipe overload rate of 100%,

or both.

- The results show that Nordre Follo municipality needs to increase their current annual rehabilitation and maintenance rate, which is currently at 0.5%, to meet the rehabilitation and maintenance needs at approximately 11.9% with the SAW method and 13.3% with TOPSIS.

In the future, SAW, TOPSIS, or other applicable MCDM techniques should be applied to a larger study area, such as the wastewater collection network for the entire Kolbotn area. This would provide a more representative pipe prioritisation for rehabilitation planning of the wastewater collection network in Kolbotn in Nordre Follo municipality. By implementing these techniques in a larger area, the rate of rehabilitation needed would also be more representable for the municipality. Additionally, incorporating criteria such as leakage data, soil type, and groundwater level could enhance the accuracy of the analysis. Especially considering that Kolbotn encounters problems with old and leaking concrete pipes in the southern parts of the network. Even though the wastewater collection network in Kolbotn is a separate system, due to the interaction between the stormwater- and the wastewater collection network, considering the stormwater network could potentially optimise the prioritisation. Lastly, the MCDM result should be accompanied by a sensitivity analysis to strengthen the robustness of the pipe prioritisation.

Further works could also investigate other advanced MCDM techniques that take interdependent criteria into consideration. These methods could be compared with the SAW and TOPSIS methods to see if the interdependencies between the criteria significantly impact the results. Also, other criteria weighting techniques, such as SWARA, Entropy, or CRITIC, could be compared with the AHP weighting method. In addition, a subjective weighting technique could be combined with an objective method to consider both expert judgment and factual data. Lastly, MCDM methods can be applied to other urban water systems, such as stormwater and water distribution networks, to prioritise pipes for rehabilitation planning. Since, wastewater, stormwater, and drinking water pipe networks often share the same corridor, the prioritisation of these urban water systems can be combined to coordinate the rehabilitation planning of these networks.

By utilising MCDM techniques to prioritise pipes for rehabilitation planning, Norwegian municipalities can facilitate proactive and sustainable asset management of the wastewater collection network. MCDM can help identify the pipes that need rehabilitation and prioritise them according to their need. This way, the pipes can be rehabilitated before pipe failure happens, which reduces the risk of service disruptions and pollution of surface, and groundwater sources. Furthermore, the municipalities can have a more reliable basis for choosing the pipes that need rehabilitation and maintenance. This will be a cost-effective way of choosing pipes for rehabilitation, as well as being able to allocate resources more efficiently. It is, however, important to have good-quality data available to optimise pipe prioritisation with MCDM techniques. SAW and TOPSIS can both be used to map the wastewater collection network and prioritise the pipes for rehabilitation and maintenance planning. Moreover, by regularly updating the MCDM methods with new data, they can be used for long-term planning of wastewater collection system rehabilitation. Consequently, the investment needed each year can be planned ahead, which could help stabilise the increase in housing charges for customers. However, to identify the accurate pipes for rehabilitation, the MCDM techniques should be combined with inspection data or other pipe condition assessment models, such as forecasting models, to validate the results. Therefore, other cities and municipalities across Norway, and other parts of the world, are recommended to implement and evaluate this methodology in their wastewater collection networks.

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Appendix A. Questionnaire Example

Questionnaire for weighting criteria with AHP

This is a questionnaire designed to collect and analyse experts' opinions on factors that affect the deterioration and rehabilitation planning of wastewater collection pipes. I am a master's student at the Norwegian University of Life Sciences (NMBU) at the Faculty of Science and Technology (REALTEK). This data will be used in my master's thesis about rehabilitation planning for wastewater collection networks by using multi-criteria decision-making (MCDM) method. MCDM is a decision-making approach that involves evaluating various alternatives based on different criteria to rank the pipes and determine the risk of failure for the pipes.

The goal of this thesis is to determine the pipes that are more critical to rehabilitation by ranking each pipe according to different criteria. Each criteria needs to be weighted based on their importance in deciding the pipes that has high emergency of rehabilitation.

* indikerer at spørsmålet er obligatorisk

For this assessment, 13 criteria have been identified. Rehabilitation planning is directly dependent on pipe deterioration. Some criteria (like diameter, age, material etc) impact the pipe deterioration and directly affect rehabilitation prioritisation. While others are essential for planning despite not directly affecting deterioration. For example, pipe renewal cost affects the renewal process, potentially leading to prioritisation decisions based on cost considerations. The criteria listed below should be pairwise compared based on their influence when prioritising pipes for rehabilitation.

Factor	Criteria	Description
Physical	Diameter	Pipe diameter of the wastewater pipe
	Pipe age	Age of the watewater pipe in years
	Length	Length of the wastewater pipe in meters
	Buried depth	The depth of the buried pipe
	Slope	Slope of the constructed pipe
	Material	Material of the wastewater pipe
Operational	Maximum velocity	The maximum velocity detected/simulated in the wastewater pipe
	Minimum velocity	The minimum velocity detected/simulated in the wastewater pipe
	Pipe overload	Number of times the pipe capacity has been exceeded
	Person equivalent	Number of people/ person equivalent connected to the pipe
	Historical failures	Number of failures due to blockage, leakage, breakage etc
Enviromental	Traffic load	Traffic intensity on the street above the pipe
Economic	Pipe renewal cost	Cost of pipe repair and/or replacement

Examples for filling the form

The approach uses the Analytic Hierarchy Process (AHP), which is an MCDM method that uses pairwise comparison for weighting the criteria. Through further calculation, I will obtain weightings for the criteria.

The AHP scale ranges from 1 to 9. In the table below, a description of each value is given. For each pair of factors, please express your expert judgement on which factor is more important by selecting values on the scale.

Numerical value	Definition	Explanation
1	Equal importance	The factors ***a*** and ***b*** contribute equally to the objective
3	Moderately importance	Slightly favor element ***a*** over ***b***
5	Strongly importance	Strongly favor element ***a*** over ***b***
7	Very strongly importance	Element ***a*** is favored very strongly over ***b***
9	Extremely importance	The evidence favoring element over ***a*** over ***b*** is of the highest possible order of importance

If the selected value is on the left side of 1, then the factor on the left side is judged more important than the one mentioned at the top of each section. Below is an example, where factor ***b*** is judged as strongly more important than factor ***a.***

With respect to Factor A *

	9	7	5	3	1	3.	5.	7.	9.
Factor B	○	○	◉	○	○	○	○	○	○

If the factor mentioned at the top is more important than the factor on the left side, then the values on the right side of 1 must be selected. Below is an example, where factor ***a*** is judged as strongly more important than factor ***b.***

With respect to Factor A *

	9	7	5	3	1	3.	5.	7.	9.
Factor B	○	○	○	○	○	○	◉	○	○

1. Name (optional)

____

2. Field of work *

Markér bare én oval.

- Municipality
- Academia
- Consultant
- Andre: ______________________

3. Spesialisation *

____

4. Educational attainment

____

5. **With respect to diameter**

Compared to the following variables, I find **diameter** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Pipe Age									
Length									
Buried Depth									
Material									
Slope									
Max. Velocity									
Min. Velocity									
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

6. **<u>With respect to pipe age:</u>**
Compared to the following variables , **I** find the **pipe age** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Length									
Buried Depth									
Material									
Slope									
Max. Velocity									
Min. Velocity									
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

7. **With respect to length**
Compared to the following variables, I find the **length** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Buried Depth									
Material									
Slope									
Max. Velocity									
Min. Velocity									
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

8. **<u>With respect to buried depth</u>**

Compared to the following variables, I find the **buried depth** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Material									
Slope									
Max. Velocity									
Min. Velocity									
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

9. **With respect to material**

Compared to the following variables, I find the **material** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Slope									
Max. Velocity									
Min. Velocity									
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

10. **With respect to slope**

Compared to the following variables, I find the **slope** to be more (rigth of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Max. Velocity	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Min. Velocity	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Pipe Overload	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Person Equivalent	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Historical Failure	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Traffic Load	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Renewal Cost	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

11. **With respect to Max. Velocity**

Compared to the following variables, I find the **maximum velocity** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Min. Velocity									
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

12. **With respect to min. velocity:**

Compared to **minimum velocity**, I find the following variables to be more (left of 1) or less (right of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Pipe Overload									
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

13. **With respect to pipe overload**
Compared to the following variables, I find the **pipe overload** to be more (right of 1) or less (le of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Person Equivalent									
Historical Failure									
Traffic Load									
Renewal Cost									

14. **With respect to Person Equivalent (PE)**
Compared to to the following variables, I find the **person equivalent** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Historical Failure									
Traffic Load									
Renewal Cost									

15. **With respect to historical failure**
Compared to the following variables, I find the **historical failure** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Traffic Load									
Renewal Cost									

16. **With respect to traffic load**
Compared to the following variables, I find the **traffic load** to be more (right of 1) or less (left of 1) important for prioritising pipes for rehabilitation:

Markér bare én oval per rad

	9	7	5	3	1	3.	5.	7.	9.
Renewal Cost	◯	◯	◯	◯	◯	◯	◯	◯	◯

17. Thank you for taking the time to answer this questionnaire. If you have any additional comments/suggestions (optional), please feel free to share them in the space provided below.

Appendix B. Decision Matrix

Table B.1: The decision matrix used for SAW and TOPSIS calculations

Pipe ID	Diameter [mm]	Pipe age [year]	Length [m]	Buried depth [m]	Material quality	Slope [%]	Min. Velocity [m/s]	Max. Velocity [m/s]	Pipe overload [%]	PE	Historical failure	Traffic load	Pipe renewal cost [NOK]
20097	230	66	61.4	2.5	Low	2.3	0.010	0.493	0	48	0	Medium	1535550
20098	230	66	62.9	2.4	Low	1.6	0.005	0.251	0	48	0	Medium	1572700
20100	230	58	61.0	2.5	Low	7.5	0.014	0.487	0	23	0	Medium	1525000
20124	230	58	22.3	2.6	Low	3.0	0.014	0.646	0	23	0	Medium	557300
20125	230	58	43.6	3.1	Low	1.4	0.012	0.381	0	23	0	Medium	1088850
20126	230	58	50.6	3.5	Low	1.0	0.009	0.418	0	23	0	Medium	1265650
20127	230	58	54.3	3.4	Low	0.4	0.006	0.206	0	37	0	Medium	1358650
20128	230	58	52.1	2.7	Low	0.9	0.002	0.002	0	37	0	Medium	1303275
20233	200	50	57.6	2.5	Low	2.5	0.008	0.327	0	42	0	Low	1438800
20234	200	50	40.5	2.5	Low	0.0	0.000	0.000	0	42	0	Low	1011275
20235	200	50	36.0	2.4	Low	3.7	0.047	0.747	0	23	1	Low	898925
20240	200	50	78.3	2.1	Low	9.9	0.042	1.858	0	8	1	Very low	1958050
20246	130	32	15.8	2.4	Very high	8.2	0.056	1.162	0	23	1	Low	395000
20247	230	32	27.3	2.4	Very high	6.8	0.056	0.964	0	23	1	Low	682975
20248	230	32	42.9	2.4	Very high	0.8	0.057	0.725	0	34	1	Low	1071300
20249	230	32	40.3	2.4	Very high	3.7	0.060	0.517	0	57	1	Low	1007200
20250	230	32	46.1	2.4	Very high	0.3	0.016	0.180	0	57	0	Low	1153525
20349	150	57	73.4	3.0	Low	3.3	0.010	0.811	0	33	0	Low	1834700
20353	100	42	11.0	2.9	High	1.8	0.007	0.821	0	17	0	Medium	274250
20361	190	42	54.4	2.8	High	2.1	0.012	0.280	0	107	1	Medium	1359875
20362	190	42	22.9	2.7	High	0.5	0.002	0.191	0	17	0	Medium	571750
20494	200	50	2.1	2.6	Low	17.8	0.008	0.442	0	39	0	Low	52225
20495	200	50	56.1	2.6	Low	1.6	0.004	0.253	0	39	0	Low	1401950
20630	230	33	67.2	2.5	Very high	6.4	0.105	0.715	0	29	0	Very low	1680050
20678	200	57	48.5	2.3	Low	0.9	0.048	0.684	100	109	1	Low	1212625
20679	200	57	59.2	2.3	Low	1.2	0.300	0.774	0	109	1	Low	1478750
20682	200	12	50.7	3.6	Low	0.6	0.001	0.138	100	115	0	Very low	1267550
20683	200	57	17.7	3.1	Low	4.6	0.002	0.140	0	115	0	Very low	442200
20707	200	57	64.8	2.4	Low	1.1	0.304	0.853	0	398	0	Low	1619050
20724	200	12	58.8	2.6	High	7.4	0.301	0.610	0	174	0	Low	1468950
20726	200	12	5.1	2.4	High	10.4	0.418	0.928	0	118	0	Low	126800
20729	150	57	41.4	2.9	Low	1.1	0.366	0.820	0	118	0	Very low	1033850
20730	150	57	56.8	3.6	Low	2.7	0.178	0.422	0	118	0	Very low	1419275
22236	250	62	43.6	3.0	Low	3.7	0.341	1.599	0	236	0	High	1308510
22244	230	66	12.6	2.5	Low	1.9	0.010	0.442	0	19	0	Medium	313950
22245	230	66	70.8	2.3	Low	3.3	0.011	0.879	0	19	0	Medium	1770825
22246	230	66	5.0	2.3	Low	5.5	0.015	1.120	0	24	0	Medium	125000
22255	200	57	84.9	2.5	Low	1.2	0.002	0.002	0	33	0	Low	2121325
22256	160	13	47.1	2.6	High	0.5	0.005	0.232	0	33	0	Low	1176825
22274	230	66	74.2	2.5	Low	1.3	0.010	0.644	0	19	0	Medium	1854175

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Table B.1 – Continued from previous page

Pipe ID	Diameter [mm]	Pipe age [year]	Length [m]	Buried depth [m]	Material quality	Slope [%]	Min. Velocity [m/s]	Max. Velocity [m/s]	Pipe overload [%]	PE	Historical failure	Traffic load	Pipe renewal cost [NOK]
22285	200	51	57.5	2.4	Low	11.4	0.070	1.305	0	145	0	Very low	1436425
22297	190	34	38.4	2.5	High	1.8	0.002	0.213	1.2	5	0	High	1152990
22299	200	51	69.9	2.3	Low	8.7	0.069	2.193	0	145	0	Very low	1746450
22304	200	51	47.9	2.2	Low	10.5	0.029	0.975	0	145	0	Very low	1197275
22305	200	51	62.6	2.2	Low	5.7	0.014	0.568	0	145	0	Very low	1564400
22317	250	46	38.2	2.5	Low	1.9	0.339	1.374	0	5	1	High	1146060
22320	250	46	44.6	2.5	Low	1.0	0.303	1.342	0	241	0	High	1337160
22323	250	46	80.1	2.5	Low	1.4	0.350	1.491	0	236	0	High	2404470
22394	200	51	52.9	2.4	Low	2.3	0.041	0.660	0	142	0	Very low	1323275
22643	200	51	49.0	2.5	Low	2.0	0.004	0.298	0	43	0	Low	1226100
22650	230	57	44.6	2.6	Low	1.2	0.008	0.350	0	30	1	Low	1115350
22651	230	57	48.5	2.5	Low	0.4	0.005	0.194	0	30	1	Low	1213450
22652	230	57	47.1	2.5	Low	0.8	0.002	0.002	0	30	1	Low	1177700
22657	200	51	41.7	2.5	Low	4.0	0.009	0.575	0	43	0	Low	1043250
22658	200	51	36.5	2.6	Low	4.4	0.009	0.488	0	20	0	Low	912625
22662	200	51	23.0	2.6	Low	4.2	0.011	0.662	0	53	0	Low	575225
22664	200	51	63.1	2.5	Low	9.0	0.013	1.081	0	20	0	Very low	1577675
22666	200	51	38.0	2.5	Low	23.9	0.013	0.762	0	304	0	Low	950075
22668	200	51	53.9	2.5	Low	4.2	0.013	0.575	0	142	0	Low	1348125
22669	200	51	46.9	2.5	Low	4.3	0.027	0.548	0	142	0	Low	1171325
22684	140	62	24.5	2.3	Very high	0.2	0.108	0.976	0	29	0	Very low	612175
22685	230	62	4.4	2.5	Low	4.7	0.108	0.504	0	29	0	Very low	110700
22693	140	6	9.9	2.8	Very high	3.9	0.109	1.150	0	29	0	Very low	247925
22694	140	33	16.1	2.8	Very high	24.0	0.109	1.417	0	29	0	Very low	402825
22697	140	33	23.3	2.3	Very high	12.8	0.108	1.342	0	29	0	Very low	583225
22701	230	66	85.2	2.4	Low	4.9	0.019	1.133	0	14	0	Medium	2130375
22702	200	51	33.4	2.4	Low	7.5	0.029	0.714	0	287	0	Very low	835375
22727	140	34	39.6	2.9	Very high	6.3	0.095	1.088	0	54	0	Very low	989700
22728	140	34	36.6	2.5	Very high	4.0	0.101	1.497	0	54	0	Very low	915875
23277	150	18	58.7	2.7	High	-0.2	0.012	0.634	21.2	49	0	Very low	1466500
23463	200	57	55.9	2.9	Low	2.0	0.008	0.370	0	33	0	Low	1396825
23466	150	57	61.2	3.0	Low	4.0	0.015	0.590	0	13	0	Low	1531125
23469	200	57	49.9	3.2	Low	1.5	0.016	0.243	0	13	0	Low	1248150
23498	200	57	64.5	2.4	Low	3.0	0.633	0.993	0	196	0	Low	1613275
23506	150	57	63.6	3.0	Low	1.6	0.002	0.002	0	118	0	Very low	1590350
25298	200	57	25.9	2.6	Low	6.8	0.438	0.977	0	118	0	Very low	647100
25519	230	32	30.7	2.5	Very high	1.1	0.015	0.405	0	7	0	Low	766425
25520	160	58	10.0	2.5	Low	2.3	0.014	0.555	0	7	0	Low	250025
25648	230	33	53.7	2.5	Very high	12.4	0.101	1.114	0	83	0	Very low	1341475
26003	150	24	15.3	2.5	High	2.1	0.005	0.459	0	25	0	High	459510
26004	150	34	75.2	2.5	High	1.0	0.001	0.307	0	25	0	High	2256180

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Table B.1 – Continued from previous page

Pipe ID	Diameter [mm]	Pipe age [year]	Length [m]	Buried depth [m]	Material quality	Slope [%]	Min. Velocity [m/s]	Max. Velocity [m/s]	Pipe overload [%]	PE	Historical failure	Traffic load	Pipe renewal cost [NOK]
32005	150	15	27.4	2.5	High	0.1	0.003	0.003	0	118	1	Very low	683925
50136	220	21	56.9	2.4	Very high	10.4	0.508	2.496	0	16	0	Medium	1422300
50138	190	21	14.1	2.5	High	9.9	0.052	0.854	0	16	0	Very low	353350
50146	240	21	46.9	2.7	High	7.6	0.520	1.827	0	16	0	Medium	1171500
50149	240	21	37.3	3.3	High	7.6	0.507	1.890	0	16	0	Medium	933725
50154	240	21	55.1	3.1	High	9.5	0.517	1.931	0	16	0	Medium	1377350
50158	240	21	67.4	3.0	High	5.9	0.524	1.919	0	37	0	Medium	1683975
50161	240	21	47.7	3.7	High	1.3	0.391	1.388	0	37	0	Medium	1191650
50162	240	21	57.7	3.6	High	0.8	0.294	1.193	0	81	0	Medium	1441275
50166	240	21	32.8	3.3	High	1.3	0.323	1.199	0	44	0	Medium	819375
50168	240	21	27.7	3.2	High	4.2	0.348	1.528	0	44	0	Medium	692175
50175	240	21	38.3	3.2	High	9.9	0.439	1.719	0	44	0	Medium	956575
50181	240	21	82.3	3.3	High	10.1	0.549	3.320	0	13	0	Medium	2056850
50182	240	21	22.5	3.3	High	4.1	0.447	1.123	0	13	0	Medium	562375
50183	240	21	23.1	3.0	High	5.5	0.016	0.422	0	17	0	Medium	577725
50184	240	21	19.2	3.3	High	3.8	0.086	0.770	0	13	0	Medium	479100
50613	150	21	62.2	2.5	High	6.4	0.003	0.409	0	30	0	Low	1555625
50618	150	21	22.7	2.5	High	7.7	0.006	0.692	0	30	0	Low	568075
50628	150	21	56.2	2.6	High	10.4	0.009	0.931	0	31	0	Low	1403975
50630	150	21	11.0	3.0	High	19.8	0.011	0.427	0	31	0	Low	275900
51229	240	21	60.3	3.3	High	1.2	0.305	1.189	0	44	0	Medium	1508550
51347	230	66	1.2	2.5	Low	14.1	0.010	0.387	0	0	0	Medium	30100
51864	150	18	33.4	2.5	High	0.4	0.001	0.001	0	59	1	Low	834550
51865	150	18	74.0	2.5	High	0.7	0.003	0.387	0	59	0	Low	1850725
51870	150	18	52.4	2.5	High	1.0	0.015	0.456	0	26	0	Low	1310100
51871	150	18	27.9	2.6	High	0.5	0.017	0.357	0	26	0	Low	698200
52938	150	13	53.8	3.2	High	2.3	0.110	0.965	0	87	0	Low	1346100
52939	150	13	81.9	3.2	High	4.5	0.044	1.308	0	87	0	Low	2047550
52942	150	13	53.8	2.5	High	0.8	0.040	0.610	0	647	0	Low	1345750
52943	150	13	54.3	2.5	High	1.5	0.040	0.613	0	854	0	Low	1356850
53234	150	13	103.5	3.2	High	3.1	0.052	1.241	0	119	0	Very low	2587800
53550	190	11	103.0	2.5	High	1.6	0.354	1.385	0	22	0	Medium	2574200
53551	190	11	51.0	2.5	High	3.7	0.336	1.222	0	23	0	Medium	1274050
53553	190	11	36.7	2.8	High	2.0	0.396	1.217	0	1	0	Medium	916775
54619	150	14	62.1	2.5	High	0.9	0.029	0.490	0	266	0	Low	1552750
54620	150	13	67.9	2.5	High	0.3	0.007	0.315	0	147	1	Low	1696975
54765	150	17	122.0	2.9	High	3.8	0.004	0.814	0	118	0	Low	3050850
55418	190	7	79.4	2.1	High	5.6	0.156	2.141	0	118	0	Medium	1985675
55419	190	7	50.2	1.7	High	1.9	0.155	1.104	0	118	0	Medium	1253925
55420	190	7	84.4	2.4	High	4.9	0.137	1.943	0	118	0	Medium	2111050
55522	140	33	11.0	2.6	Very high	20.8	0.109	1.888	0	29	0	Very low	275000

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Table B.1 – Continued from previous page

Pipe ID	Diameter [mm]	Pipe age [year]	Length [m]	Buried depth [m]	Material quality	Slope [%]	Min. Velocity [m/s]	Max. Velocity [m/s]	Pipe overload [%]	PE	Historical failure	Traffic load	Pipe renewal cost [NOK]
55524	140	33	15.6	2.6	Very high	2.0	0.109	1.314	0	29	0	Very low	388975
55583	220	21	57.8	2.5	Very high	6.0	0.356	2.242	0	150	0	Medium	1445100
91357	150	21	57.5	2.6	High	5.8	0.006	0.682	0	61	0	Low	1437950
91744	150	13	66.5	2.8	High	0.5	0.025	0.731	0	33	0	Low	1662900
91837	150	13	65.2	2.9	High	2.5	0.110	1.421	0	87	0	Medium	1630550
91948	150	13	99.8	2.5	High	1.0	0.035	0.609	0	119	0	Low	2494025
92057	190	11	47.0	2.5	High	2.2	0.316	1.139	0	1	0	Medium	1175750
92697	150	30	54.6	6.4	High	16.6	0.002	0.207	0	16	0	Very low	1363875
92698	150	18	57.6	2.3	High	0.9	0.012	0.540	21.7	73	1	Low	1439400
95437	190	4	3.1	2.4	High	8.7	0.303	0.752	0	0	0	Low	77200
95438	190	4	105.3	2.5	High	3.8	0.011	1.149	3.1	115	0	Very low	2631625
95808	150	13	39.7	2.5	High	0.5	0.002	0.177	100	203	0	Low	992150
95438_A	190	4	51.8	2.5	High	0.4	0.071	0.853	3.1	22	0	Very low	1294950

Appendix C. Calculations SAW

C.1 Normalised Decision Matrix

Table C.1: The normalised decision matrix with the SAW method using Equations (3.11) and (3.12)

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
20097	0,133	1,000	0,498	0,833	1,000	0,9044	0,9850	0,149	0,000	0,056	0,000	0,667	0,5016
20098	0,133	1,000	0,511	0,865	1,000	0,9345	0,9926	0,076	0,000	0,056	0,000	0,667	0,4893
20100	0,133	0,871	0,495	0,833	1,000	0,6860	0,9779	0,147	0,000	0,027	0,000	0,667	0,5051
20124	0,133	0,871	0,175	0,811	1,000	0,8749	0,9780	0,195	0,000	0,027	0,000	0,667	0,8255
20125	0,133	0,871	0,350	0,701	1,000	0,9426	0,9815	0,115	0,000	0,027	0,000	0,667	0,6495
20126	0,133	0,871	0,409	0,616	1,000	0,9564	0,9851	0,126	0,000	0,027	0,000	0,667	0,5910
20127	0,133	0,871	0,440	0,640	1,000	0,9839	0,9910	0,062	0,000	0,043	0,000	0,667	0,5602
20128	0,133	0,871	0,421	0,801	1,000	0,9617	0,9967	0,001	0,000	0,043	0,000	0,667	0,5785
20233	0,333	0,742	0,466	0,830	1,000	0,8951	0,9878	0,099	0,000	0,049	0,000	0,333	0,5337
20234	0,333	0,742	0,325	0,841	1,000	1,0000	1,0000	0,000	0,000	0,049	0,000	0,333	0,6752
20235	0,333	0,742	0,288	0,859	1,000	0,8460	0,9253	0,225	0,000	0,027	1,000	0,333	0,7124
20240	0,333	0,742	0,638	0,926	1,000	0,5873	0,9335	0,560	0,000	0,009	1,000	0,000	0,3618
20246	0,800	0,452	0,121	0,854	0,000	0,6601	0,9112	0,350	0,000	0,027	1,000	0,333	0,8792
20247	0,133	0,452	0,216	0,849	0,000	0,7150	0,9120	0,290	0,000	0,027	1,000	0,333	0,7839
20248	0,133	0,452	0,345	0,854	0,000	0,9650	0,9102	0,218	0,000	0,040	1,000	0,333	0,6553
20249	0,133	0,452	0,323	0,844	0,000	0,8461	0,9047	0,156	0,000	0,067	1,000	0,333	0,6765
20250	0,133	0,452	0,372	0,844	0,000	0,9857	0,9752	0,054	0,000	0,067	0,000	0,333	0,6281
20349	0,667	0,855	0,597	0,719	1,000	0,8638	0,9850	0,244	0,000	0,039	0,000	0,333	0,4026
20353	1,000	0,613	0,081	0,754	0,333	0,9241	0,9897	0,247	0,000	0,020	0,000	0,667	0,9192
20361	0,400	0,613	0,440	0,766	0,333	0,9127	0,9807	0,084	0,000	0,125	1,000	0,667	0,5598
20362	0,400	0,613	0,179	0,793	0,333	0,9800	0,9973	0,057	0,000	0,020	0,000	0,667	0,8207
20494	0,333	0,742	0,007	0,820	1,000	0,2606	0,9878	0,133	0,000	0,046	0,000	0,333	0,9927
20495	0,333	0,742	0,454	0,813	1,000	0,9318	0,9940	0,076	0,000	0,046	0,000	0,333	0,5459
20630	0,133	0,468	0,546	0,833	0,000	0,7344	0,8349	0,215	0,000	0,034	0,000	0,000	0,4538
20678	0,333	0,855	0,391	0,869	1,000	0,9622	0,9243	0,206	1,000	0,128	1,000	0,333	0,6085
20679	0,333	0,855	0,480	0,871	1,000	0,9500	0,5267	0,233	0,000	0,128	1,000	0,333	0,5204
20682	0,333	0,129	0,410	0,595	1,000	0,9745	0,9984	0,042	1,000	0,135	0,000	0,000	0,5904
20683	0,333	0,855	0,136	0,705	1,000	0,8093	0,9973	0,042	0,000	0,135	0,000	0,000	0,8636
20707	0,333	0,855	0,526	0,858	1,000	0,9524	0,5201	0,257	0,000	0,466	0,000	0,333	0,4740
20724	0,333	0,129	0,476	0,808	0,333	0,6932	0,5248	0,184	0,000	0,204	0,000	0,333	0,5237
20726	0,333	0,129	0,032	0,851	0,333	0,5649	0,3398	0,279	0,000	0,138	0,000	0,333	0,9680
20729	0,667	0,855	0,332	0,743	1,000	0,9547	0,4213	0,247	0,000	0,138	0,000	0,000	0,6677
20730	0,667	0,855	0,460	0,606	1,000	0,8871	0,7190	0,127	0,000	0,138	0,000	0,000	0,5401
22236	0,000	0,935	0,351	0,736	1,000	0,8444	0,4619	0,482	0,000	0,276	0,000	1,000	0,5768
22244	0,133	1,000	0,094	0,834	1,000	0,9204	0,9848	0,133	0,000	0,022	0,000	0,667	0,9060
22245	0,133	1,000	0,576	0,875	1,000	0,8636	0,9832	0,265	0,000	0,022	0,000	0,667	0,4237
22246	0,133	1,000	0,031	0,886	1,000	0,7723	0,9768	0,337	0,000	0,028	0,000	0,667	0,9686
22255	0,333	0,855	0,692	0,833	1,000	0,9490	0,9973	0,001	0,000	0,039	0,000	0,333	0,3077

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Table C.1 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
22256	0,600	0,145	0,380	0,811	0,333	0,9805	0,9923	0,070	0,000	0,039	0,000	0,333	0,6204
22274	0,133	1,000	0,604	0,838	1,000	0,9467	0,9850	0,194	0,000	0,022	0,000	0,667	0,3962
22285	0,333	0,758	0,466	0,854	1,000	0,5261	0,8902	0,393	0,000	0,170	0,000	0,000	0,5344
22297	0,400	0,484	0,308	0,833	0,333	0,9232	0,9967	0,064	0,012	0,006	0,000	1,000	0,6283
22299	0,333	0,758	0,568	0,879	1,000	0,6388	0,8903	0,661	0,000	0,170	0,000	0,000	0,4318
22304	0,333	0,758	0,386	0,891	1,000	0,5610	0,9550	0,294	0,000	0,170	0,000	0,000	0,6136
22305	0,333	0,758	0,508	0,905	1,000	0,7645	0,9776	0,171	0,000	0,170	0,000	0,000	0,4921
22317	0,000	0,677	0,306	0,833	1,000	0,9215	0,4649	0,414	0,000	0,006	1,000	1,000	0,6306
22320	0,000	0,677	0,359	0,833	1,000	0,9580	0,5213	0,404	0,000	0,282	0,000	1,000	0,5673
22323	0,000	0,677	0,653	0,833	1,000	0,9423	0,4477	0,449	0,000	0,276	0,000	1,000	0,2140
22394	0,333	0,758	0,428	0,844	1,000	0,9025	0,9355	0,199	0,000	0,166	0,000	0,000	0,5719
22643	0,333	0,758	0,396	0,833	1,000	0,9168	0,9934	0,090	0,000	0,050	0,000	0,333	0,6041
22650	0,133	0,855	0,359	0,806	1,000	0,9493	0,9875	0,105	0,000	0,035	1,000	0,333	0,6407
22651	0,133	0,855	0,392	0,833	1,000	0,9828	0,9923	0,058	0,000	0,035	1,000	0,333	0,6083
22652	0,133	0,855	0,380	0,833	1,000	0,9670	0,9968	0,001	0,000	0,035	1,000	0,333	0,6201
22657	0,333	0,758	0,335	0,833	1,000	0,8324	0,9866	0,173	0,000	0,050	0,000	0,333	0,6646
22658	0,333	0,758	0,292	0,817	1,000	0,8164	0,9866	0,147	0,000	0,023	0,000	0,333	0,7078
22662	0,333	0,758	0,180	0,817	1,000	0,8263	0,9834	0,199	0,000	0,062	0,000	0,333	0,8195
22664	0,333	0,758	0,512	0,833	1,000	0,6262	0,9802	0,326	0,000	0,023	0,000	0,000	0,4877
22666	0,333	0,758	0,305	0,833	1,000	0,0059	0,9801	0,229	0,000	0,356	0,000	0,333	0,6954
22668	0,333	0,758	0,436	0,833	1,000	0,8247	0,9801	0,173	0,000	0,166	0,000	0,333	0,5637
22669	0,333	0,758	0,378	0,833	1,000	0,8214	0,9578	0,165	0,000	0,166	0,000	0,333	0,6222
22684	0,733	0,935	0,193	0,886	0,000	0,9898	0,8289	0,294	0,000	0,034	0,000	0,000	0,8073
22685	0,133	0,935	0,027	0,833	1,000	0,8025	0,8295	0,152	0,000	0,034	0,000	0,000	0,9733
22693	0,733	0,032	0,072	0,764	0,000	0,8363	0,8274	0,347	0,000	0,034	0,000	0,000	0,9279
22694	0,733	0,468	0,123	0,761	0,000	0,0000	0,8277	0,427	0,000	0,034	0,000	0,000	0,8766
22697	0,733	0,468	0,183	0,886	0,000	0,4651	0,8287	0,404	0,000	0,034	0,000	0,000	0,8169
22701	0,133	1,000	0,695	0,851	1,000	0,7967	0,9708	0,341	0,000	0,016	0,000	0,667	0,3047
22702	0,333	0,758	0,267	0,844	1,000	0,6860	0,9550	0,215	0,000	0,336	0,000	0,000	0,7334
22727	0,733	0,484	0,318	0,758	0,000	0,7362	0,8492	0,328	0,000	0,063	0,000	0,000	0,6823
22728	0,733	0,484	0,293	0,833	0,000	0,8334	0,8402	0,451	0,000	0,063	0,000	0,000	0,7068
23277	0,667	0,226	0,476	0,790	0,333	1,0000	0,9807	0,191	0,212	0,057	0,000	0,000	0,5245
23463	0,333	0,855	0,452	0,736	1,000	0,9158	0,9875	0,111	0,000	0,039	0,000	0,333	0,5476
23466	0,667	0,855	0,497	0,719	1,000	0,8321	0,9771	0,178	0,000	0,015	0,000	0,333	0,5031
23469	0,333	0,855	0,403	0,683	1,000	0,9383	0,9750	0,073	0,000	0,015	0,000	0,333	0,5968
23498	0,333	0,855	0,524	0,850	1,000	0,8742	0,0000	0,299	0,000	0,230	0,000	0,333	0,4759
23506	0,667	0,855	0,517	0,726	1,000	0,9339	0,9975	0,001	0,000	0,138	0,000	0,000	0,4835
25298	0,333	0,855	0,204	0,811	1,000	0,7185	0,3082	0,294	0,000	0,138	0,000	0,000	0,7957
25519	0,133	0,452	0,244	0,833	0,000	0,9530	0,9766	0,122	0,000	0,008	0,000	0,333	0,7562
25520	0,600	0,871	0,073	0,833	1,000	0,9026	0,9777	0,167	0,000	0,008	0,000	0,333	0,9272
25648	0,133	0,468	0,434	0,833	0,000	0,4841	0,8401	0,336	0,000	0,097	0,000	0,000	0,5659
26003	0,667	0,323	0,117	0,833	0,333	0,9144	0,9923	0,138	0,000	0,029	0,000	1,000	0,8578

Continued on next page

Table C.1 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
26004	0,667	0,484	0,612	0,833	0,333	0,9593	0,9981	0,092	0,000	0,029	0,000	1,000	0,2631
32005	0,667	0,177	0,216	0,833	0,333	0,9954	0,9960	0,001	0,000	0,138	1,000	0,000	0,7836
50136	0,200	0,274	0,461	0,852	0,000	0,5665	0,1967	0,752	0,000	0,019	0,000	0,667	0,5391
50138	0,400	0,274	0,107	0,839	0,333	0,5876	0,9180	0,257	0,000	0,019	0,000	0,000	0,8930
50146	0,067	0,274	0,378	0,792	0,333	0,6855	0,1779	0,550	0,000	0,019	0,000	0,667	0,6221
50149	0,067	0,274	0,299	0,660	0,333	0,6856	0,1988	0,569	0,000	0,019	0,000	0,667	0,7009
50154	0,067	0,274	0,446	0,703	0,333	0,6048	0,1832	0,582	0,000	0,019	0,000	0,667	0,5540
50158	0,067	0,274	0,548	0,715	0,333	0,7552	0,1719	0,578	0,000	0,043	0,000	0,667	0,4525
50161	0,067	0,274	0,385	0,585	0,333	0,9467	0,3826	0,418	0,000	0,043	0,000	0,667	0,6155
50162	0,067	0,274	0,467	0,599	0,333	0,9653	0,5362	0,359	0,000	0,095	0,000	0,667	0,5328
50166	0,067	0,274	0,261	0,670	0,333	0,9479	0,4891	0,361	0,000	0,052	0,000	0,667	0,7387
50168	0,067	0,274	0,219	0,680	0,333	0,8271	0,4504	0,460	0,000	0,052	0,000	0,667	0,7808
50175	0,067	0,274	0,307	0,678	0,333	0,5876	0,3063	0,518	0,000	0,052	0,000	0,667	0,6933
50181	0,067	0,274	0,671	0,656	0,333	0,5795	0,1321	1,000	0,000	0,015	0,000	0,667	0,3291
50182	0,067	0,274	0,176	0,672	0,333	0,8279	0,2944	0,338	0,000	0,015	0,000	0,667	0,8238
50183	0,067	0,274	0,181	0,715	0,333	0,7712	0,9753	0,127	0,000	0,020	0,000	0,667	0,8187
50184	0,067	0,274	0,149	0,667	0,333	0,8436	0,8636	0,232	0,000	0,015	0,000	0,667	0,8514
50613	0,667	0,274	0,505	0,838	0,333	0,7317	0,9954	0,123	0,000	0,035	0,000	0,333	0,4950
50618	0,667	0,274	0,178	0,833	0,333	0,6812	0,9907	0,208	0,000	0,035	0,000	0,333	0,8219
50628	0,667	0,274	0,455	0,817	0,333	0,5663	0,9859	0,280	0,000	0,036	0,000	0,333	0,5452
50630	0,667	0,274	0,081	0,736	0,333	0,1738	0,9820	0,129	0,000	0,036	0,000	0,333	0,9186
51229	0,067	0,274	0,489	0,669	0,333	0,9517	0,5185	0,358	0,000	0,052	0,000	0,667	0,5106
51347	0,133	1,000	0,000	0,834	1,000	0,4121	0,9848	0,116	0,000	0,000	0,000	0,667	1,0000
51864	0,667	0,226	0,266	0,823	0,333	0,9825	0,9992	0,000	0,000	0,069	1,000	0,333	0,7337
51865	0,667	0,226	0,603	0,827	0,333	0,9691	0,9946	0,117	0,000	0,069	0,000	0,333	0,3973
51870	0,667	0,226	0,424	0,827	0,333	0,9563	0,9769	0,137	0,000	0,030	0,000	0,333	0,5763
51871	0,667	0,226	0,221	0,801	0,333	0,9806	0,9728	0,107	0,000	0,030	0,000	0,333	0,7788
52938	0,667	0,145	0,436	0,694	0,333	0,9026	0,8268	0,291	0,000	0,102	0,000	0,333	0,5643
52939	0,667	0,145	0,668	0,694	0,333	0,8119	0,9300	0,394	0,000	0,102	0,000	0,333	0,3321
52942	0,667	0,145	0,436	0,833	0,333	0,9652	0,9369	0,184	0,000	0,758	0,000	0,333	0,5645
52943	0,667	0,145	0,439	0,833	0,333	0,9371	0,9369	0,185	0,000	1,000	0,000	0,333	0,5608
53234	0,667	0,145	0,847	0,694	0,333	0,8700	0,9174	0,374	0,000	0,139	0,000	0,000	0,1533
53550	0,400	0,113	0,842	0,832	0,333	0,9321	0,4399	0,417	0,000	0,026	0,000	0,667	0,1578
53551	0,400	0,113	0,412	0,833	0,333	0,8472	0,4687	0,368	0,000	0,027	0,000	0,667	0,5882
53553	0,400	0,113	0,294	0,758	0,333	0,9155	0,3736	0,367	0,000	0,001	0,000	0,667	0,7065
54619	0,667	0,161	0,504	0,833	0,333	0,9625	0,9543	0,148	0,000	0,311	0,000	0,333	0,4959
54620	0,667	0,145	0,552	0,833	0,333	0,9872	0,9886	0,095	0,000	0,172	1,000	0,333	0,4482
54765	0,667	0,210	1,000	0,756	0,333	0,8397	0,9943	0,245	0,000	0,138	0,000	0,333	0,0000
55418	0,400	0,048	0,647	0,918	0,333	0,7688	0,7541	0,645	0,000	0,138	0,000	0,667	0,3526
55419	0,400	0,048	0,405	1,000	0,333	0,9220	0,7549	0,333	0,000	0,138	0,000	0,667	0,5949
55420	0,400	0,048	0,689	0,854	0,333	0,7954	0,7838	0,585	0,000	0,138	0,000	0,667	0,3111
55522	0,733	0,468	0,081	0,811	0,000	0,1351	0,8281	0,569	0,000	0,034	0,000	0,000	0,9189

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Table C.1 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
55524	0,733	0,468	0,119	0,811	0,000	0,9149	0,8282	0,396	0,000	0,034	0,000	0,000	0,8812
55583	0,200	0,274	0,468	0,833	0,000	0,7510	0,4371	0,675	0,000	0,176	0,000	0,667	0,5316
91357	0,667	0,274	0,466	0,822	0,333	0,7604	0,9907	0,205	0,000	0,071	0,000	0,333	0,5339
91744	0,667	0,145	0,541	0,779	0,333	0,9772	0,9599	0,220	0,000	0,039	0,000	0,333	0,4595
91837	0,667	0,145	0,530	0,752	0,333	0,8946	0,8266	0,428	0,000	0,102	0,000	0,667	0,4702
91948	0,667	0,145	0,816	0,833	0,333	0,9587	0,9452	0,183	0,000	0,139	0,000	0,333	0,1843
92057	0,400	0,113	0,379	0,833	0,333	0,9101	0,5005	0,343	0,000	0,001	0,000	0,667	0,6207
92697	0,667	0,419	0,442	0,000	0,333	0,3086	0,9970	0,062	0,000	0,019	0,000	0,000	0,5585
92698	0,667	0,226	0,467	0,876	0,333	0,9638	0,9817	0,163	0,217	0,085	1,000	0,333	0,5335
95437	0,400	0,000	0,016	0,857	0,333	0,6373	0,5205	0,226	0,000	0,000	0,000	0,333	0,9844
95438	0,400	0,000	0,861	0,823	0,333	0,8430	0,9828	0,346	0,031	0,135	0,000	0,000	0,1388
95808	0,667	0,145	0,318	0,833	0,333	0,9784	0,9965	0,053	1,000	0,238	0,000	0,333	0,6815
95438_A	0,400	0,000	0,419	0,822	0,333	0,9822	0,8881	0,257	0,031	0,026	0,000	0,000	0,5813

C.2 Weighted Normalised Decision Matrix

Table C.2: The weighted normalised decision matrix with the SAW method using Equation (3.13)

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost	Total score	Rank
20097	0,0038	0,0751	0,0143	0,0333	0,0548	0,0247	0,0280	0,0038	0,0000	0,0037	0,0000	0,0603	0,0872	0,3891	32
20098	0,0038	0,0751	0,0147	0,0346	0,0548	0,0256	0,0282	0,0019	0,0000	0,0037	0,0000	0,0603	0,0851	0,3878	33
20100	0,0038	0,0654	0,0142	0,0333	0,0548	0,0188	0,0278	0,0037	0,0000	0,0018	0,0000	0,0603	0,0879	0,3718	41
20124	0,0038	0,0654	0,0050	0,0325	0,0548	0,0239	0,0278	0,0049	0,0000	0,0018	0,0000	0,0603	0,1436	0,4238	22
20125	0,0038	0,0654	0,0101	0,0281	0,0548	0,0258	0,0279	0,0029	0,0000	0,0018	0,0000	0,0603	0,1130	0,3938	30
20126	0,0038	0,0654	0,0118	0,0246	0,0548	0,0262	0,0280	0,0032	0,0000	0,0018	0,0000	0,0603	0,1028	0,3826	36
20127	0,0038	0,0654	0,0126	0,0256	0,0548	0,0269	0,0281	0,0016	0,0000	0,0028	0,0000	0,0603	0,0974	0,3795	37
20128	0,0038	0,0654	0,0121	0,0320	0,0548	0,0263	0,0283	0,0000	0,0000	0,0028	0,0000	0,0603	0,1006	0,3866	34
20233	0,0094	0,0558	0,0134	0,0332	0,0548	0,0245	0,0281	0,0025	0,0000	0,0032	0,0000	0,0302	0,0928	0,3479	60
20234	0,0094	0,0558	0,0093	0,0337	0,0548	0,0273	0,0284	0,0000	0,0000	0,0032	0,0000	0,0302	0,1174	0,3696	45
20235	0,0094	0,0558	0,0083	0,0344	0,0548	0,0231	0,0263	0,0057	0,0000	0,0018	0,2450	0,0302	0,1239	0,6186	3
20240	0,0094	0,0558	0,0183	0,0371	0,0548	0,0161	0,0265	0,0142	0,0000	0,0006	0,2450	0,0000	0,0629	0,5406	13
20246	0,0226	0,0339	0,0035	0,0342	0,0000	0,0180	0,0259	0,0088	0,0000	0,0018	0,2450	0,0302	0,1529	0,5768	9
20247	0,0038	0,0339	0,0062	0,0340	0,0000	0,0195	0,0259	0,0073	0,0000	0,0018	0,2450	0,0302	0,1363	0,5439	12
20248	0,0038	0,0339	0,0099	0,0342	0,0000	0,0264	0,0259	0,0055	0,0000	0,0026	0,2450	0,0302	0,1140	0,5313	15
20249	0,0038	0,0339	0,0093	0,0338	0,0000	0,0231	0,0257	0,0039	0,0000	0,0044	0,2450	0,0302	0,1177	0,5307	16
20250	0,0038	0,0339	0,0107	0,0338	0,0000	0,0270	0,0277	0,0014	0,0000	0,0044	0,0000	0,0302	0,1092	0,2820	109
20349	0,0189	0,0642	0,0172	0,0288	0,0548	0,0236	0,0280	0,0062	0,0000	0,0025	0,0000	0,0302	0,0700	0,3444	62
20353	0,0283	0,0461	0,0023	0,0301	0,0183	0,0253	0,0281	0,0063	0,0000	0,0013	0,0000	0,0603	0,1599	0,4062	26
20361	0,0113	0,0461	0,0127	0,0307	0,0183	0,0250	0,0279	0,0021	0,0000	0,0082	0,2450	0,0603	0,0974	0,5848	8
20362	0,0113	0,0461	0,0052	0,0317	0,0183	0,0268	0,0283	0,0015	0,0000	0,0013	0,0000	0,0603	0,1427	0,3735	40
20494	0,0094	0,0558	0,0002	0,0328	0,0548	0,0071	0,0281	0,0034	0,0000	0,0030	0,0000	0,0302	0,1727	0,3974	27
20495	0,0094	0,0558	0,0131	0,0325	0,0548	0,0255	0,0282	0,0019	0,0000	0,0030	0,0000	0,0302	0,0949	0,3493	59
20630	0,0038	0,0351	0,0157	0,0333	0,0000	0,0201	0,0237	0,0054	0,0000	0,0022	0,0000	0,0000	0,0789	0,2183	131
20678	0,0094	0,0642	0,0113	0,0348	0,0548	0,0263	0,0263	0,0052	0,1169	0,0084	0,2450	0,0302	0,1058	0,7385	1
20679	0,0094	0,0642	0,0138	0,0349	0,0548	0,0260	0,0150	0,0059	0,0000	0,0084	0,2450	0,0302	0,0905	0,5980	7
20682	0,0094	0,0097	0,0118	0,0238	0,0548	0,0266	0,0284	0,0011	0,1169	0,0088	0,0000	0,0000	0,1027	0,3940	29
20683	0,0094	0,0642	0,0039	0,0282	0,0548	0,0221	0,0283	0,0011	0,0000	0,0088	0,0000	0,0000	0,1502	0,3712	43
20707	0,0094	0,0642	0,0151	0,0343	0,0548	0,0260	0,0148	0,0065	0,0000	0,0306	0,0000	0,0302	0,0824	0,3685	47
20724	0,0094	0,0097	0,0137	0,0323	0,0183	0,0190	0,0149	0,0046	0,0000	0,0134	0,0000	0,0302	0,0911	0,2566	124
20726	0,0094	0,0097	0,0009	0,0340	0,0183	0,0154	0,0096	0,0071	0,0000	0,0091	0,0000	0,0302	0,1684	0,3121	85
20729	0,0189	0,0642	0,0096	0,0297	0,0548	0,0261	0,0120	0,0062	0,0000	0,0091	0,0000	0,0000	0,1161	0,3467	61
20730	0,0189	0,0642	0,0132	0,0242	0,0548	0,0243	0,0204	0,0032	0,0000	0,0091	0,0000	0,0000	0,0939	0,3263	72
22236	0,0000	0,0703	0,0101	0,0295	0,0548	0,0231	0,0131	0,0122	0,0000	0,0181	0,0000	0,0905	0,1003	0,4220	23
22244	0,0038	0,0751	0,0027	0,0334	0,0548	0,0252	0,0280	0,0034	0,0000	0,0015	0,0000	0,0603	0,1576	0,4457	19
22245	0,0038	0,0751	0,0166	0,0350	0,0548	0,0236	0,0279	0,0067	0,0000	0,0015	0,0000	0,0603	0,0737	0,3791	38
22246	0,0038	0,0751	0,0009	0,0354	0,0548	0,0211	0,0277	0,0085	0,0000	0,0018	0,0000	0,0603	0,1685	0,4581	18

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Table C.2 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost	Total score	Rank
22255	0,0094	0,0642	0,0199	0,0333	0,0548	0,0259	0,0283	0,0000	0,0000	0,0025	0,0000	0,0302	0,0535	0,3222	75
22256	0,0170	0,0109	0,0109	0,0325	0,0183	0,0268	0,0282	0,0018	0,0000	0,0025	0,0000	0,0302	0,1079	0,2869	105
22274	0,0038	0,0751	0,0174	0,0335	0,0548	0,0259	0,0280	0,0049	0,0000	0,0015	0,0000	0,0603	0,0689	0,3741	39
22285	0,0094	0,0570	0,0134	0,0342	0,0548	0,0144	0,0253	0,0099	0,0000	0,0111	0,0000	0,0000	0,0930	0,3225	74
22297	0,0113	0,0364	0,0089	0,0333	0,0183	0,0252	0,0283	0,0016	0,0014	0,0004	0,0000	0,0905	0,1093	0,3649	49
22299	0,0094	0,0570	0,0163	0,0351	0,0548	0,0175	0,0253	0,0167	0,0000	0,0111	0,0000	0,0000	0,0751	0,3184	79
22304	0,0094	0,0570	0,0111	0,0357	0,0548	0,0153	0,0271	0,0074	0,0000	0,0111	0,0000	0,0000	0,1067	0,3358	65
22305	0,0094	0,0570	0,0146	0,0362	0,0548	0,0209	0,0278	0,0043	0,0000	0,0111	0,0000	0,0000	0,0856	0,3218	76
22317	0,0000	0,0509	0,0088	0,0333	0,0548	0,0252	0,0132	0,0105	0,0000	0,0004	0,2450	0,0905	0,1097	0,6422	2
22320	0,0000	0,0509	0,0103	0,0333	0,0548	0,0262	0,0148	0,0102	0,0000	0,0185	0,0000	0,0905	0,0987	0,4083	25
22323	0,0000	0,0509	0,0188	0,0333	0,0548	0,0258	0,0127	0,0114	0,0000	0,0181	0,0000	0,0905	0,0372	0,3535	57
22394	0,0094	0,0570	0,0123	0,0338	0,0548	0,0247	0,0266	0,0050	0,0000	0,0109	0,0000	0,0000	0,0995	0,3340	67
22643	0,0094	0,0570	0,0114	0,0333	0,0548	0,0251	0,0282	0,0023	0,0000	0,0033	0,0000	0,0302	0,1051	0,3600	53
22650	0,0038	0,0642	0,0103	0,0322	0,0548	0,0260	0,0280	0,0027	0,0000	0,0023	0,2450	0,0302	0,1114	0,6109	4
22651	0,0038	0,0642	0,0113	0,0333	0,0548	0,0269	0,0282	0,0015	0,0000	0,0023	0,2450	0,0302	0,1058	0,6072	5
22652	0,0038	0,0642	0,0109	0,0333	0,0548	0,0264	0,0283	0,0000	0,0000	0,0023	0,2450	0,0302	0,1079	0,6071	6
22657	0,0094	0,0570	0,0096	0,0333	0,0548	0,0228	0,0280	0,0044	0,0000	0,0033	0,0000	0,0302	0,1156	0,3684	48
22658	0,0094	0,0570	0,0084	0,0327	0,0548	0,0223	0,0280	0,0037	0,0000	0,0015	0,0000	0,0302	0,1231	0,3712	44
22662	0,0094	0,0570	0,0052	0,0327	0,0548	0,0226	0,0279	0,0050	0,0000	0,0041	0,0000	0,0302	0,1425	0,3915	31
22664	0,0094	0,0570	0,0147	0,0333	0,0548	0,0171	0,0278	0,0082	0,0000	0,0015	0,0000	0,0000	0,0848	0,3088	86
22666	0,0094	0,0570	0,0088	0,0333	0,0548	0,0002	0,0278	0,0058	0,0000	0,0234	0,0000	0,0302	0,1210	0,3716	42
22668	0,0094	0,0570	0,0125	0,0333	0,0548	0,0226	0,0278	0,0044	0,0000	0,0109	0,0000	0,0302	0,0980	0,3610	51
22669	0,0094	0,0570	0,0109	0,0333	0,0548	0,0225	0,0272	0,0042	0,0000	0,0109	0,0000	0,0302	0,1082	0,3685	46
22684	0,0208	0,0703	0,0055	0,0354	0,0000	0,0271	0,0235	0,0074	0,0000	0,0022	0,0000	0,0000	0,1404	0,3327	68
22685	0,0038	0,0703	0,0008	0,0333	0,0548	0,0219	0,0236	0,0038	0,0000	0,0022	0,0000	0,0000	0,1693	0,3838	35
22693	0,0208	0,0024	0,0021	0,0306	0,0000	0,0229	0,0235	0,0088	0,0000	0,0022	0,0000	0,0000	0,1614	0,2746	117
22694	0,0208	0,0351	0,0035	0,0305	0,0000	0,0000	0,0235	0,0108	0,0000	0,0022	0,0000	0,0000	0,1525	0,2789	112
22697	0,0208	0,0351	0,0053	0,0354	0,0000	0,0127	0,0235	0,0102	0,0000	0,0022	0,0000	0,0000	0,1421	0,2874	103
22701	0,0038	0,0751	0,0200	0,0341	0,0548	0,0218	0,0276	0,0086	0,0000	0,0011	0,0000	0,0603	0,0530	0,3602	52
22702	0,0094	0,0570	0,0077	0,0338	0,0548	0,0188	0,0271	0,0054	0,0000	0,0221	0,0000	0,0000	0,1276	0,3636	50
22727	0,0208	0,0364	0,0091	0,0303	0,0000	0,0201	0,0241	0,0083	0,0000	0,0042	0,0000	0,0000	0,1187	0,2719	118
22728	0,0208	0,0364	0,0084	0,0333	0,0000	0,0228	0,0239	0,0114	0,0000	0,0042	0,0000	0,0000	0,1229	0,2840	107
23277	0,0189	0,0170	0,0137	0,0316	0,0183	0,0273	0,0279	0,0048	0,0248	0,0038	0,0000	0,0000	0,0912	0,2792	111
23463	0,0094	0,0642	0,0130	0,0295	0,0548	0,0250	0,0280	0,0028	0,0000	0,0025	0,0000	0,0302	0,0952	0,3548	55
23466	0,0189	0,0642	0,0143	0,0288	0,0548	0,0228	0,0277	0,0045	0,0000	0,0010	0,0000	0,0302	0,0875	0,3547	56
23469	0,0094	0,0642	0,0116	0,0273	0,0548	0,0257	0,0277	0,0019	0,0000	0,0010	0,0000	0,0302	0,1038	0,3576	54
23498	0,0094	0,0642	0,0151	0,0340	0,0548	0,0239	0,0000	0,0076	0,0000	0,0151	0,0000	0,0302	0,0828	0,3370	64
23506	0,0189	0,0642	0,0148	0,0290	0,0548	0,0255	0,0283	0,0000	0,0000	0,0091	0,0000	0,0000	0,0841	0,3289	71
25298	0,0094	0,0642	0,0059	0,0325	0,0548	0,0196	0,0088	0,0074	0,0000	0,0091	0,0000	0,0000	0,1384	0,3501	58
25519	0,0038	0,0339	0,0070	0,0333	0,0000	0,0261	0,0277	0,0031	0,0000	0,0005	0,0000	0,0302	0,1315	0,2971	94
25520	0,0170	0,0654	0,0021	0,0333	0,0548	0,0247	0,0278	0,0042	0,0000	0,0005	0,0000	0,0302	0,1613	0,4213	24

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Table C.2 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost	Total score	Rank
25648	0,0038	0,0351	0,0125	0,0333	0,0000	0,0132	0,0239	0,0085	0,0000	0,0064	0,0000	0,0000	0,0984	0,2351	128
26003	0,0189	0,0242	0,0034	0,0333	0,0183	0,0250	0,0282	0,0035	0,0000	0,0019	0,0000	0,0905	0,1492	0,3964	28
26004	0,0189	0,0364	0,0176	0,0333	0,0183	0,0262	0,0283	0,0023	0,0000	0,0019	0,0000	0,0905	0,0458	0,3195	78
32005	0,0189	0,0133	0,0062	0,0333	0,0183	0,0272	0,0283	0,0000	0,0000	0,0091	0,2450	0,0000	0,1363	0,5359	14
50136	0,0057	0,0206	0,0132	0,0341	0,0000	0,0155	0,0056	0,0190	0,0000	0,0012	0,0000	0,0603	0,0938	0,2690	120
50138	0,0113	0,0206	0,0031	0,0336	0,0183	0,0161	0,0261	0,0065	0,0000	0,0012	0,0000	0,0000	0,1553	0,2920	98
50146	0,0019	0,0206	0,0109	0,0317	0,0183	0,0187	0,0051	0,0139	0,0000	0,0012	0,0000	0,0603	0,1082	0,2908	100
50149	0,0019	0,0206	0,0086	0,0264	0,0183	0,0187	0,0056	0,0144	0,0000	0,0012	0,0000	0,0603	0,1219	0,2980	93
50154	0,0019	0,0206	0,0128	0,0281	0,0183	0,0165	0,0052	0,0147	0,0000	0,0012	0,0000	0,0603	0,0964	0,2761	115
50158	0,0019	0,0206	0,0157	0,0286	0,0183	0,0206	0,0049	0,0146	0,0000	0,0028	0,0000	0,0603	0,0787	0,2671	121
50161	0,0019	0,0206	0,0111	0,0234	0,0183	0,0259	0,0109	0,0106	0,0000	0,0028	0,0000	0,0603	0,1070	0,2928	97
50162	0,0019	0,0206	0,0134	0,0240	0,0183	0,0264	0,0152	0,0091	0,0000	0,0062	0,0000	0,0603	0,0927	0,2881	102
50166	0,0019	0,0206	0,0075	0,0268	0,0183	0,0259	0,0139	0,0091	0,0000	0,0034	0,0000	0,0603	0,1285	0,3162	83
50168	0,0019	0,0206	0,0063	0,0272	0,0183	0,0226	0,0128	0,0116	0,0000	0,0034	0,0000	0,0603	0,1358	0,3208	77
50175	0,0019	0,0206	0,0088	0,0271	0,0183	0,0161	0,0087	0,0131	0,0000	0,0034	0,0000	0,0603	0,1206	0,2989	91
50181	0,0019	0,0206	0,0193	0,0263	0,0183	0,0158	0,0038	0,0253	0,0000	0,0010	0,0000	0,0603	0,0572	0,2498	125
50182	0,0019	0,0206	0,0051	0,0269	0,0183	0,0226	0,0084	0,0086	0,0000	0,0010	0,0000	0,0603	0,1433	0,3169	82
50183	0,0019	0,0206	0,0052	0,0286	0,0183	0,0211	0,0277	0,0032	0,0000	0,0013	0,0000	0,0603	0,1424	0,3306	69
50184	0,0019	0,0206	0,0043	0,0267	0,0183	0,0231	0,0245	0,0059	0,0000	0,0010	0,0000	0,0603	0,1481	0,3346	66
50613	0,0189	0,0206	0,0145	0,0335	0,0183	0,0200	0,0283	0,0031	0,0000	0,0023	0,0000	0,0302	0,0861	0,2758	116
50618	0,0189	0,0206	0,0051	0,0333	0,0183	0,0186	0,0281	0,0053	0,0000	0,0023	0,0000	0,0302	0,1430	0,3236	73
50628	0,0189	0,0206	0,0131	0,0327	0,0183	0,0155	0,0280	0,0071	0,0000	0,0024	0,0000	0,0302	0,0948	0,2814	110
50630	0,0189	0,0206	0,0023	0,0295	0,0183	0,0048	0,0279	0,0033	0,0000	0,0024	0,0000	0,0302	0,1598	0,3178	80
51229	0,0019	0,0206	0,0141	0,0268	0,0183	0,0260	0,0147	0,0091	0,0000	0,0034	0,0000	0,0603	0,0888	0,2839	108
51347	0,0038	0,0751	0,0000	0,0334	0,0548	0,0113	0,0280	0,0029	0,0000	0,0000	0,0000	0,0603	0,1739	0,4435	20
51864	0,0189	0,0170	0,0077	0,0329	0,0183	0,0269	0,0284	0,0000	0,0000	0,0045	0,2450	0,0302	0,1276	0,5572	11
51865	0,0189	0,0170	0,0173	0,0331	0,0183	0,0265	0,0282	0,0029	0,0000	0,0045	0,0000	0,0302	0,0691	0,2660	123
51870	0,0189	0,0170	0,0122	0,0331	0,0183	0,0261	0,0277	0,0035	0,0000	0,0020	0,0000	0,0302	0,1002	0,2892	101
51871	0,0189	0,0170	0,0064	0,0320	0,0183	0,0268	0,0276	0,0027	0,0000	0,0020	0,0000	0,0302	0,1355	0,3173	81
52938	0,0189	0,0109	0,0125	0,0278	0,0183	0,0247	0,0235	0,0073	0,0000	0,0067	0,0000	0,0302	0,0982	0,2789	113
52939	0,0189	0,0109	0,0192	0,0278	0,0183	0,0222	0,0264	0,0100	0,0000	0,0067	0,0000	0,0302	0,0578	0,2482	126
52942	0,0189	0,0109	0,0125	0,0333	0,0183	0,0264	0,0266	0,0046	0,0000	0,0497	0,0000	0,0302	0,0982	0,3296	70
52943	0,0189	0,0109	0,0126	0,0333	0,0183	0,0256	0,0266	0,0047	0,0000	0,0656	0,0000	0,0302	0,0975	0,3442	63
53234	0,0189	0,0109	0,0243	0,0278	0,0183	0,0238	0,0261	0,0095	0,0000	0,0091	0,0000	0,0000	0,0267	0,1952	134
53550	0,0113	0,0085	0,0242	0,0333	0,0183	0,0255	0,0125	0,0105	0,0000	0,0017	0,0000	0,0603	0,0274	0,2336	130
53551	0,0113	0,0085	0,0118	0,0333	0,0183	0,0232	0,0133	0,0093	0,0000	0,0018	0,0000	0,0603	0,1023	0,2934	96
53553	0,0113	0,0085	0,0084	0,0303	0,0183	0,0250	0,0106	0,0093	0,0000	0,0001	0,0000	0,0603	0,1229	0,3050	88
54619	0,0189	0,0121	0,0145	0,0333	0,0183	0,0263	0,0271	0,0037	0,0000	0,0204	0,0000	0,0302	0,0863	0,2911	99
54620	0,0189	0,0109	0,0159	0,0333	0,0183	0,0270	0,0281	0,0024	0,0000	0,0113	0,2450	0,0302	0,0780	0,5191	17
54765	0,0189	0,0158	0,0287	0,0302	0,0183	0,0230	0,0282	0,0062	0,0000	0,0091	0,0000	0,0302	0,0000	0,2085	133
55418	0,0113	0,0036	0,0186	0,0367	0,0183	0,0210	0,0214	0,0163	0,0000	0,0091	0,0000	0,0603	0,0613	0,2781	114

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Table C.2 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost	Total score	Rank
55419	0,0113	0,0036	0,0116	0,0400	0,0183	0,0252	0,0214	0,0084	0,0000	0,0091	0,0000	0,0603	0,1035	0,3128	84
55420	0,0113	0,0036	0,0198	0,0342	0,0183	0,0217	0,0223	0,0148	0,0000	0,0091	0,0000	0,0603	0,0541	0,2695	119
55522	0,0208	0,0351	0,0023	0,0325	0,0000	0,0037	0,0235	0,0144	0,0000	0,0022	0,0000	0,0000	0,1598	0,2943	95
55524	0,0208	0,0351	0,0034	0,0325	0,0000	0,0250	0,0235	0,0100	0,0000	0,0022	0,0000	0,0000	0,1533	0,3058	87
55583	0,0057	0,0206	0,0135	0,0333	0,0000	0,0205	0,0124	0,0171	0,0000	0,0115	0,0000	0,0603	0,0925	0,2874	104
91357	0,0189	0,0206	0,0134	0,0329	0,0183	0,0208	0,0281	0,0052	0,0000	0,0047	0,0000	0,0302	0,0929	0,2859	106
91744	0,0189	0,0109	0,0155	0,0312	0,0183	0,0267	0,0273	0,0056	0,0000	0,0025	0,0000	0,0302	0,0799	0,2669	122
91837	0,0189	0,0109	0,0152	0,0301	0,0183	0,0245	0,0235	0,0108	0,0000	0,0067	0,0000	0,0603	0,0818	0,3010	90
91948	0,0189	0,0109	0,0234	0,0333	0,0183	0,0262	0,0268	0,0046	0,0000	0,0091	0,0000	0,0302	0,0321	0,2339	129
92057	0,0113	0,0085	0,0109	0,0333	0,0183	0,0249	0,0142	0,0087	0,0000	0,0001	0,0000	0,0603	0,1080	0,2984	92
92697	0,0189	0,0315	0,0127	0,0000	0,0183	0,0084	0,0283	0,0016	0,0000	0,0012	0,0000	0,0000	0,0971	0,2180	132
92698	0,0189	0,0170	0,0134	0,0351	0,0183	0,0264	0,0279	0,0041	0,0254	0,0056	0,2450	0,0302	0,0928	0,5598	10
95437	0,0113	0,0000	0,0004	0,0343	0,0183	0,0174	0,0148	0,0057	0,0000	0,0000	0,0000	0,0302	0,1712	0,3037	89
95438	0,0113	0,0000	0,0248	0,0329	0,0183	0,0231	0,0279	0,0088	0,0036	0,0088	0,0000	0,0000	0,0241	0,1836	135
95808	0,0189	0,0109	0,0092	0,0333	0,0183	0,0268	0,0283	0,0013	0,1169	0,0156	0,0000	0,0302	0,1185	0,4281	21
95438_A	0,0113	0,0000	0,0120	0,0329	0,0183	0,0269	0,0252	0,0065	0,0036	0,0017	0,0000	0,0000	0,1011	0,2395	127

Appendix D. Calculations TOPSIS

D.1 Normalised Decision Matrix

Table D.1: The normalised decision matrix with the TOPSIS method using Equation (3.14)

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
20097	0,133	1,000	0,498	0,833	1,000	0,9044	0,9850	0,149	0,000	0,056	0,000	0,667	0,5016
20098	0,133	1,000	0,511	0,865	1,000	0,9345	0,9926	0,076	0,000	0,056	0,000	0,667	0,4893
20100	0,133	0,871	0,495	0,833	1,000	0,6860	0,9779	0,147	0,000	0,027	0,000	0,667	0,5051
20124	0,133	0,871	0,175	0,811	1,000	0,8749	0,9780	0,195	0,000	0,027	0,000	0,667	0,8255
20125	0,133	0,871	0,350	0,701	1,000	0,9426	0,9815	0,115	0,000	0,027	0,000	0,667	0,6495
20126	0,133	0,871	0,409	0,616	1,000	0,9564	0,9851	0,126	0,000	0,027	0,000	0,667	0,5910
20127	0,133	0,871	0,440	0,640	1,000	0,9839	0,9910	0,062	0,000	0,043	0,000	0,667	0,5602
20128	0,133	0,871	0,421	0,801	1,000	0,9617	0,9967	0,001	0,000	0,043	0,000	0,667	0,5785
20233	0,333	0,742	0,466	0,830	1,000	0,8951	0,9878	0,099	0,000	0,049	0,000	0,333	0,5337
20234	0,333	0,742	0,325	0,841	1,000	1,0000	1,0000	0,000	0,000	0,049	0,000	0,333	0,6752
20235	0,333	0,742	0,288	0,859	1,000	0,8460	0,9253	0,225	0,000	0,027	1,000	0,333	0,7124
20240	0,333	0,742	0,638	0,926	1,000	0,5873	0,9335	0,560	0,000	0,009	1,000	0,000	0,3618
20246	0,800	0,452	0,121	0,854	0,000	0,6601	0,9112	0,350	0,000	0,027	1,000	0,333	0,8792
20247	0,133	0,452	0,216	0,849	0,000	0,7150	0,9120	0,290	0,000	0,027	1,000	0,333	0,7839
20248	0,133	0,452	0,345	0,854	0,000	0,9650	0,9102	0,218	0,000	0,040	1,000	0,333	0,6553
20249	0,133	0,452	0,323	0,844	0,000	0,8461	0,9047	0,156	0,000	0,067	1,000	0,333	0,6765
20250	0,133	0,452	0,372	0,844	0,000	0,9857	0,9752	0,054	0,000	0,067	0,000	0,333	0,6281
20349	0,667	0,855	0,597	0,719	1,000	0,8638	0,9850	0,244	0,000	0,039	0,000	0,333	0,4026
20353	1,000	0,613	0,081	0,754	0,333	0,9241	0,9897	0,247	0,000	0,020	0,000	0,667	0,9192
20361	0,400	0,613	0,440	0,766	0,333	0,9127	0,9807	0,084	0,000	0,125	1,000	0,667	0,5598
20362	0,400	0,613	0,179	0,793	0,333	0,9800	0,9973	0,057	0,000	0,020	0,000	0,667	0,8207
20494	0,333	0,742	0,007	0,820	1,000	0,2606	0,9878	0,133	0,000	0,046	0,000	0,333	0,9927
20495	0,333	0,742	0,454	0,813	1,000	0,9318	0,9940	0,076	0,000	0,046	0,000	0,333	0,5459
20630	0,133	0,468	0,546	0,833	0,000	0,7344	0,8349	0,215	0,000	0,034	0,000	0,000	0,4538
20678	0,333	0,855	0,391	0,869	1,000	0,9622	0,9243	0,206	1,000	0,128	1,000	0,333	0,6085
20679	0,333	0,855	0,480	0,871	1,000	0,9500	0,5267	0,233	0,000	0,128	1,000	0,333	0,5204
20682	0,333	0,129	0,410	0,595	1,000	0,9745	0,9984	0,042	1,000	0,135	0,000	0,000	0,5904
20683	0,333	0,855	0,136	0,705	1,000	0,8093	0,9973	0,042	0,000	0,135	0,000	0,000	0,8636
20707	0,333	0,855	0,526	0,858	1,000	0,9524	0,5201	0,257	0,000	0,466	0,000	0,333	0,4740
20724	0,333	0,129	0,476	0,808	0,333	0,6932	0,5248	0,184	0,000	0,204	0,000	0,333	0,5237
20726	0,333	0,129	0,032	0,851	0,333	0,5649	0,3398	0,279	0,000	0,138	0,000	0,333	0,9680
20729	0,667	0,855	0,332	0,743	1,000	0,9547	0,4213	0,247	0,000	0,138	0,000	0,000	0,6677
20730	0,667	0,855	0,460	0,606	1,000	0,8871	0,7190	0,127	0,000	0,138	0,000	0,000	0,5401
22236	0,000	0,935	0,351	0,736	1,000	0,8444	0,4619	0,482	0,000	0,276	0,000	1,000	0,5768
22244	0,133	1,000	0,094	0,834	1,000	0,9204	0,9848	0,133	0,000	0,022	0,000	0,667	0,9060
22245	0,133	1,000	0,576	0,875	1,000	0,8636	0,9832	0,265	0,000	0,022	0,000	0,667	0,4237
22246	0,133	1,000	0,031	0,886	1,000	0,7723	0,9768	0,337	0,000	0,028	0,000	0,667	0,9686
22255	0,333	0,855	0,692	0,833	1,000	0,9490	0,9973	0,001	0,000	0,039	0,000	0,333	0,3077

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Table D.1 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
22256	0,600	0,145	0,380	0,811	0,333	0,9805	0,9923	0,070	0,000	0,039	0,000	0,333	0,6204
22274	0,133	1,000	0,604	0,838	1,000	0,9467	0,9850	0,194	0,000	0,022	0,000	0,667	0,3962
22285	0,333	0,758	0,466	0,854	1,000	0,5261	0,8902	0,393	0,000	0,170	0,000	0,000	0,5344
22297	0,400	0,484	0,308	0,833	0,333	0,9232	0,9967	0,064	0,012	0,006	0,000	1,000	0,6283
22299	0,333	0,758	0,568	0,879	1,000	0,6388	0,8903	0,661	0,000	0,170	0,000	0,000	0,4318
22304	0,333	0,758	0,386	0,891	1,000	0,5610	0,9550	0,294	0,000	0,170	0,000	0,000	0,6136
22305	0,333	0,758	0,508	0,905	1,000	0,7645	0,9776	0,171	0,000	0,170	0,000	0,000	0,4921
22317	0,000	0,677	0,306	0,833	1,000	0,9215	0,4649	0,414	0,000	0,006	1,000	1,000	0,6306
22320	0,000	0,677	0,359	0,833	1,000	0,9580	0,5213	0,404	0,000	0,282	0,000	1,000	0,5673
22323	0,000	0,677	0,653	0,833	1,000	0,9423	0,4477	0,449	0,000	0,276	0,000	1,000	0,2140
22394	0,333	0,758	0,428	0,844	1,000	0,9025	0,9355	0,199	0,000	0,166	0,000	0,000	0,5719
22643	0,333	0,758	0,396	0,833	1,000	0,9168	0,9934	0,090	0,000	0,050	0,000	0,333	0,6041
22650	0,133	0,855	0,359	0,806	1,000	0,9493	0,9875	0,105	0,000	0,035	1,000	0,333	0,6407
22651	0,133	0,855	0,392	0,833	1,000	0,9828	0,9923	0,058	0,000	0,035	1,000	0,333	0,6083
22652	0,133	0,855	0,380	0,833	1,000	0,9670	0,9968	0,001	0,000	0,035	1,000	0,333	0,6201
22657	0,333	0,758	0,335	0,833	1,000	0,8324	0,9866	0,173	0,000	0,050	0,000	0,333	0,6646
22658	0,333	0,758	0,292	0,817	1,000	0,8164	0,9866	0,147	0,000	0,023	0,000	0,333	0,7078
22662	0,333	0,758	0,180	0,817	1,000	0,8263	0,9834	0,199	0,000	0,062	0,000	0,333	0,8195
22664	0,333	0,758	0,512	0,833	1,000	0,6262	0,9802	0,326	0,000	0,023	0,000	0,000	0,4877
22666	0,333	0,758	0,305	0,833	1,000	0,0059	0,9801	0,229	0,000	0,356	0,000	0,333	0,6954
22668	0,333	0,758	0,436	0,833	1,000	0,8247	0,9801	0,173	0,000	0,166	0,000	0,333	0,5637
22669	0,333	0,758	0,378	0,833	1,000	0,8214	0,9578	0,165	0,000	0,166	0,000	0,333	0,6222
22684	0,733	0,935	0,193	0,886	0,000	0,9898	0,8289	0,294	0,000	0,034	0,000	0,000	0,8073
22685	0,133	0,935	0,027	0,833	1,000	0,8025	0,8295	0,152	0,000	0,034	0,000	0,000	0,9733
22693	0,733	0,032	0,072	0,764	0,000	0,8363	0,8274	0,347	0,000	0,034	0,000	0,000	0,9279
22694	0,733	0,468	0,123	0,761	0,000	0,0000	0,8277	0,427	0,000	0,034	0,000	0,000	0,8766
22697	0,733	0,468	0,183	0,886	0,000	0,4651	0,8287	0,404	0,000	0,034	0,000	0,000	0,8169
22701	0,133	1,000	0,695	0,851	1,000	0,7967	0,9708	0,341	0,000	0,016	0,000	0,667	0,3047
22702	0,333	0,758	0,267	0,844	1,000	0,6860	0,9550	0,215	0,000	0,336	0,000	0,000	0,7334
22727	0,733	0,484	0,318	0,758	0,000	0,7362	0,8492	0,328	0,000	0,063	0,000	0,000	0,6823
22728	0,733	0,484	0,293	0,833	0,000	0,8334	0,8402	0,451	0,000	0,063	0,000	0,000	0,7068
23277	0,667	0,226	0,476	0,790	0,333	1,0000	0,9807	0,191	0,212	0,057	0,000	0,000	0,5245
23463	0,333	0,855	0,452	0,736	1,000	0,9158	0,9875	0,111	0,000	0,039	0,000	0,333	0,5476
23466	0,667	0,855	0,497	0,719	1,000	0,8321	0,9771	0,178	0,000	0,015	0,000	0,333	0,5031
23469	0,333	0,855	0,403	0,683	1,000	0,9383	0,9750	0,073	0,000	0,015	0,000	0,333	0,5968
23498	0,333	0,855	0,524	0,850	1,000	0,8742	0,0000	0,299	0,000	0,230	0,000	0,333	0,4759
23506	0,667	0,855	0,517	0,726	1,000	0,9339	0,9975	0,001	0,000	0,138	0,000	0,000	0,4835
25298	0,333	0,855	0,204	0,811	1,000	0,7185	0,3082	0,294	0,000	0,138	0,000	0,000	0,7957
25519	0,133	0,452	0,244	0,833	0,000	0,9530	0,9766	0,122	0,000	0,008	0,000	0,333	0,7562
25520	0,600	0,871	0,073	0,833	1,000	0,9026	0,9777	0,167	0,000	0,008	0,000	0,333	0,9272
25648	0,133	0,468	0,434	0,833	0,000	0,4841	0,8401	0,336	0,000	0,097	0,000	0,000	0,5659
26003	0,667	0,323	0,117	0,833	0,333	0,9144	0,9923	0,138	0,000	0,029	0,000	1,000	0,8578

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Table D.1 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
26004	0,667	0,484	0,612	0,833	0,333	0,9593	0,9981	0,092	0,000	0,029	0,000	1,000	0,2631
32005	0,667	0,177	0,216	0,833	0,333	0,9954	0,9960	0,001	0,000	0,138	1,000	0,000	0,7836
50136	0,200	0,274	0,461	0,852	0,000	0,5665	0,1967	0,752	0,000	0,019	0,000	0,667	0,5391
50138	0,400	0,274	0,107	0,839	0,333	0,5876	0,9180	0,257	0,000	0,019	0,000	0,000	0,8930
50146	0,067	0,274	0,378	0,792	0,333	0,6855	0,1779	0,550	0,000	0,019	0,000	0,667	0,6221
50149	0,067	0,274	0,299	0,660	0,333	0,6856	0,1988	0,569	0,000	0,019	0,000	0,667	0,7009
50154	0,067	0,274	0,446	0,703	0,333	0,6048	0,1832	0,582	0,000	0,019	0,000	0,667	0,5540
50158	0,067	0,274	0,548	0,715	0,333	0,7552	0,1719	0,578	0,000	0,043	0,000	0,667	0,4525
50161	0,067	0,274	0,385	0,585	0,333	0,9467	0,3826	0,418	0,000	0,043	0,000	0,667	0,6155
50162	0,067	0,274	0,467	0,599	0,333	0,9653	0,5362	0,359	0,000	0,095	0,000	0,667	0,5328
50166	0,067	0,274	0,261	0,670	0,333	0,9479	0,4891	0,361	0,000	0,052	0,000	0,667	0,7387
50168	0,067	0,274	0,219	0,680	0,333	0,8271	0,4504	0,460	0,000	0,052	0,000	0,667	0,7808
50175	0,067	0,274	0,307	0,678	0,333	0,5876	0,3063	0,518	0,000	0,052	0,000	0,667	0,6933
50181	0,067	0,274	0,671	0,656	0,333	0,5795	0,1321	1,000	0,000	0,015	0,000	0,667	0,3291
50182	0,067	0,274	0,176	0,672	0,333	0,8279	0,2944	0,338	0,000	0,015	0,000	0,667	0,8238
50183	0,067	0,274	0,181	0,715	0,333	0,7712	0,9753	0,127	0,000	0,020	0,000	0,667	0,8187
50184	0,067	0,274	0,149	0,667	0,333	0,8436	0,8636	0,232	0,000	0,015	0,000	0,667	0,8514
50613	0,667	0,274	0,505	0,838	0,333	0,7317	0,9954	0,123	0,000	0,035	0,000	0,333	0,4950
50618	0,667	0,274	0,178	0,833	0,333	0,6812	0,9907	0,208	0,000	0,035	0,000	0,333	0,8219
50628	0,667	0,274	0,455	0,817	0,333	0,5663	0,9859	0,280	0,000	0,036	0,000	0,333	0,5452
50630	0,667	0,274	0,081	0,736	0,333	0,1738	0,9820	0,129	0,000	0,036	0,000	0,333	0,9186
51229	0,067	0,274	0,489	0,669	0,333	0,9517	0,5185	0,358	0,000	0,052	0,000	0,667	0,5106
51347	0,133	1,000	0,000	0,834	1,000	0,4121	0,9848	0,116	0,000	0,000	0,000	0,667	1,0000
51864	0,667	0,226	0,266	0,823	0,333	0,9825	0,9992	0,000	0,000	0,069	1,000	0,333	0,7337
51865	0,667	0,226	0,603	0,827	0,333	0,9691	0,9946	0,117	0,000	0,069	0,000	0,333	0,3973
51870	0,667	0,226	0,424	0,827	0,333	0,9563	0,9769	0,137	0,000	0,030	0,000	0,333	0,5763
51871	0,667	0,226	0,221	0,801	0,333	0,9806	0,9728	0,107	0,000	0,030	0,000	0,333	0,7788
52938	0,667	0,145	0,436	0,694	0,333	0,9026	0,8268	0,291	0,000	0,102	0,000	0,333	0,5643
52939	0,667	0,145	0,668	0,694	0,333	0,8119	0,9300	0,394	0,000	0,102	0,000	0,333	0,3321
52942	0,667	0,145	0,436	0,833	0,333	0,9652	0,9369	0,184	0,000	0,758	0,000	0,333	0,5645
52943	0,667	0,145	0,439	0,833	0,333	0,9371	0,9369	0,185	0,000	1,000	0,000	0,333	0,5608
53234	0,667	0,145	0,847	0,694	0,333	0,8700	0,9174	0,374	0,000	0,139	0,000	0,000	0,1533
53550	0,400	0,113	0,842	0,832	0,333	0,9321	0,4399	0,417	0,000	0,026	0,000	0,667	0,1578
53551	0,400	0,113	0,412	0,833	0,333	0,8472	0,4687	0,368	0,000	0,027	0,000	0,667	0,5882
53553	0,400	0,113	0,294	0,758	0,333	0,9155	0,3736	0,367	0,000	0,001	0,000	0,667	0,7065
54619	0,667	0,161	0,504	0,833	0,333	0,9625	0,9543	0,148	0,000	0,311	0,000	0,333	0,4959
54620	0,667	0,145	0,552	0,833	0,333	0,9872	0,9886	0,095	0,000	0,172	1,000	0,333	0,4482
54765	0,667	0,210	1,000	0,756	0,333	0,8397	0,9943	0,245	0,000	0,138	0,000	0,333	0,0000
55418	0,400	0,048	0,647	0,918	0,333	0,7688	0,7541	0,645	0,000	0,138	0,000	0,667	0,3526
55419	0,400	0,048	0,405	1,000	0,333	0,9220	0,7549	0,333	0,000	0,138	0,000	0,667	0,5949
55420	0,400	0,048	0,689	0,854	0,333	0,7954	0,7838	0,585	0,000	0,138	0,000	0,667	0,3111
55522	0,733	0,468	0,081	0,811	0,000	0,1351	0,8281	0,569	0,000	0,034	0,000	0,000	0,9189

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Table D.1 – Continued from previous page

Pipe ID	Diameter	Pipe age	Length	Buried depth	Material quality	Slope	Min. Velocity	Max. Velocity	Pipe overload	PE	Historical failure	Traffic load	Pipe renewal cost
55524	0,733	0,468	0,119	0,811	0,000	0,9149	0,8282	0,396	0,000	0,034	0,000	0,000	0,8812
55583	0,200	0,274	0,468	0,833	0,000	0,7510	0,4371	0,675	0,000	0,176	0,000	0,667	0,5316
91357	0,667	0,274	0,466	0,822	0,333	0,7604	0,9907	0,205	0,000	0,071	0,000	0,333	0,5339
91744	0,667	0,145	0,541	0,779	0,333	0,9772	0,9599	0,220	0,000	0,039	0,000	0,333	0,4595
91837	0,667	0,145	0,530	0,752	0,333	0,8946	0,8266	0,428	0,000	0,102	0,000	0,667	0,4702
91948	0,667	0,145	0,816	0,833	0,333	0,9587	0,9452	0,183	0,000	0,139	0,000	0,333	0,1843
92057	0,400	0,113	0,379	0,833	0,333	0,9101	0,5005	0,343	0,000	0,001	0,000	0,667	0,6207
92697	0,667	0,419	0,442	0,000	0,333	0,3086	0,9970	0,062	0,000	0,019	0,000	0,000	0,5585
92698	0,667	0,226	0,467	0,876	0,333	0,9638	0,9817	0,163	0,217	0,085	1,000	0,333	0,5335
95437	0,400	0,000	0,016	0,857	0,333	0,6373	0,5205	0,226	0,000	0,000	0,000	0,333	0,9844
95438	0,400	0,000	0,861	0,823	0,333	0,8430	0,9828	0,346	0,031	0,135	0,000	0,000	0,1388
95808	0,667	0,145	0,318	0,833	0,333	0,9784	0,9965	0,053	1,000	0,238	0,000	0,333	0,6815
95438_A	0,400	0,000	0,419	0,822	0,333	0,9822	0,8881	0,257	0,031	0,026	0,000	0,000	0,5813

D.2 Identification of Ideal Solutions

Table D.2: The ideal-best and ideal-worst solutions identified for each criterion using Equations (3.16) and (3.17).

	Diameter [mm]	Pipe age [year]	Length [m]	Buried depth [m]	Material quality	Slope [%]	Minimum Velocity [m/s]	Maximum Velocity [m/s]	Pipe overload rate [%]	PE	Historical failure	Traffic load	Pipe renewal cost [NOK]
Ideal best	0.00124	0.01052	0.00569	0.00217	0.00094	0.00000	0.00000	0.00708	0.06647	0.03623	0.05941	0.01455	0.00034
Ideal worst	0.00310	0.00064	0.00006	0.00808	0.00659	0.00864	0.00787	0.00000	0.00000	0.00000	0.00000	0.00208	0.03404

D.3 Ranking of the Pipes

Table D.3: Calculation of the separation measures (Equation (3.18) and (3.19)) and the proximity degree (Equation (3.20)) for ranking of the pipes with the TOPSIS method

Pipe ID	$\sum_j (v_j^+ - v_{ij}^2)$	S^+	$\sum_j (v_j^- - v_{ij}^2)$	S^-	C	Rank
20097	0.0095	0.0974	0.0006	0.0247	0.2023	85
20098	0.0095	0.0975	0.0006	0.0246	0.2012	87
20100	0.0096	0.0979	0.0006	0.0237	0.1949	94
20124	0.0093	0.0966	0.0011	0.0326	0.2521	37
20125	0.0094	0.0972	0.0008	0.0278	0.2223	61
20126	0.0095	0.0974	0.0007	0.0262	0.2122	72
20127	0.0095	0.0974	0.0007	0.0256	0.2082	75
20128	0.0095	0.0973	0.0007	0.0262	0.2119	73
20233	0.0095	0.0977	0.0005	0.0234	0.1936	95
20234	0.0094	0.0971	0.0008	0.0275	0.2208	63
20235	0.0059	0.0769	0.0043	0.0657	0.4607	9
20240	0.0064	0.0799	0.0039	0.0622	0.4377	19
20246	0.0058	0.0764	0.0046	0.0678	0.4703	5
20247	0.0059	0.0766	0.0044	0.0665	0.4646	7
20248	0.0059	0.0769	0.0042	0.0651	0.4586	13
20249	0.0058	0.0764	0.0043	0.0653	0.4607	10
20250	0.0094	0.0970	0.0007	0.0262	0.2124	71
20349	0.0097	0.0985	0.0004	0.0206	0.1729	121
20353	0.0093	0.0965	0.0012	0.0351	0.2667	27
20361	0.0057	0.0757	0.0042	0.0646	0.4605	11
20362	0.0093	0.0967	0.0010	0.0323	0.2503	38
20494	0.0094	0.0968	0.0013	0.0358	0.2702	24
20495	0.0095	0.0977	0.0006	0.0238	0.1962	92
20630	0.0097	0.0987	0.0004	0.0202	0.1699	124
20678	0.0013	0.0364	0.0086	0.0929	0.7188	1
20679	0.0058	0.0764	0.0041	0.0638	0.4551	17
20682	0.0050	0.0709	0.0050	0.0706	0.4990	4
20683	0.0092	0.0960	0.0011	0.0327	0.2542	34
20707	0.0088	0.0938	0.0008	0.0274	0.2262	58
20724	0.0092	0.0962	0.0005	0.0220	0.1862	111
20726	0.0092	0.0958	0.0012	0.0344	0.2643	29
20729	0.0093	0.0965	0.0007	0.0266	0.2164	66
20730	0.0094	0.0970	0.0005	0.0232	0.1933	97
22236	0.0089	0.0945	0.0008	0.0286	0.2326	54
22244	0.0093	0.0966	0.0012	0.0353	0.2679	26
22245	0.0097	0.0983	0.0005	0.0230	0.1894	103
22246	0.0093	0.0964	0.0014	0.0370	0.2774	23
22255	0.0099	0.0993	0.0004	0.0191	0.1616	128
22256	0.0095	0.0976	0.0006	0.0252	0.2051	79
22274	0.0097	0.0985	0.0005	0.0226	0.1866	110
22285	0.0093	0.0966	0.0005	0.0230	0.1922	99
22297	0.0094	0.0969	0.0008	0.0282	0.2254	59
22299	0.0094	0.0971	0.0004	0.0211	0.1784	117
22304	0.0093	0.0963	0.0006	0.0253	0.2079	76
22305	0.0094	0.0969	0.0005	0.0226	0.1891	105

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Table D.3 – Continued from previous page

Pipe ID	$\sum_j (v_j^+ - v_{ij}^2)$	S^+	$\sum_j (v_j^- - v_{ij}^2)$	S^-	**C**	**Rank**
22317	0.0060	0.0772	0.0043	0.0655	0.4590	12
22320	0.0089	0.0945	0.0008	0.0281	0.2295	55
22323	0.0094	0.0971	0.0005	0.0219	0.1840	114
22394	0.0093	0.0965	0.0006	0.0247	0.2041	84
22643	0.0095	0.0973	0.0006	0.0254	0.2069	77
22650	0.0059	0.0771	0.0042	0.0651	0.4579	14
22651	0.0060	0.0773	0.0042	0.0648	0.4561	16
22652	0.0060	0.0773	0.0042	0.0649	0.4566	15
22657	0.0094	0.0970	0.0007	0.0268	0.2166	65
22658	0.0095	0.0973	0.0008	0.0279	0.2232	60
22662	0.0093	0.0965	0.0010	0.0313	0.2449	44
22664	0.0097	0.0987	0.0005	0.0213	0.1776	118
22666	0.0088	0.0939	0.0009	0.0296	0.2399	47
22668	0.0092	0.0961	0.0006	0.0248	0.2049	81
22669	0.0092	0.0958	0.0007	0.0262	0.2148	69
22684	0.0094	0.0970	0.0010	0.0318	0.2466	41
22685	0.0094	0.0971	0.0013	0.0358	0.2691	25
22693	0.0095	0.0974	0.0011	0.0337	0.2570	32
22694	0.0095	0.0974	0.0010	0.0317	0.2452	43
22697	0.0095	0.0972	0.0009	0.0302	0.2368	49
22701	0.0098	0.0992	0.0004	0.0206	0.1720	122
22702	0.0089	0.0941	0.0009	0.0306	0.2454	42
22727	0.0094	0.0972	0.0007	0.0265	0.2145	70
22728	0.0094	0.0970	0.0008	0.0276	0.2215	62
23277	0.0080	0.0892	0.0007	0.0265	0.2289	56
23463	0.0095	0.0977	0.0006	0.0241	0.1978	90
23466	0.0097	0.0982	0.0005	0.0227	0.1878	106
23469	0.0096	0.0978	0.0006	0.0253	0.2055	78
23498	0.0092	0.0961	0.0005	0.0226	0.1904	101
23506	0.0095	0.0973	0.0005	0.0227	0.1893	104
25298	0.0092	0.0961	0.0009	0.0298	0.2367	50
25519	0.0095	0.0973	0.0009	0.0295	0.2329	53
25520	0.0094	0.0970	0.0012	0.0349	0.2643	28
25648	0.0095	0.0973	0.0005	0.0229	0.1908	100
26003	0.0093	0.0965	0.0012	0.0342	0.2614	31
26004	0.0099	0.0994	0.0004	0.0210	0.1744	120
32005	0.0057	0.0758	0.0044	0.0666	0.4677	6
50136	0.0096	0.0979	0.0005	0.0229	0.1897	102
50138	0.0095	0.0975	0.0010	0.0322	0.2481	40
50146	0.0095	0.0976	0.0006	0.0247	0.2019	86
50149	0.0095	0.0973	0.0007	0.0268	0.2163	67
50154	0.0096	0.0979	0.0005	0.0226	0.1874	108
50158	0.0096	0.0981	0.0004	0.0204	0.1718	123
50161	0.0095	0.0972	0.0006	0.0250	0.2045	83
50162	0.0094	0.0969	0.0005	0.0232	0.1931	98
50166	0.0093	0.0966	0.0008	0.0286	0.2286	57
50168	0.0093	0.0965	0.0009	0.0296	0.2349	51
50175	0.0094	0.0969	0.0007	0.0265	0.2150	68
50181	0.0099	0.0994	0.0003	0.0179	0.1525	130
50182	0.0094	0.0970	0.0009	0.0307	0.2402	46
50183	0.0094	0.0969	0.0010	0.0312	0.2438	45

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Table D.3 – Continued from previous page

Pipe ID	$\sum_j (v_j^+ - v_{ij}^2)$	S^+	$\sum_j (v_j^- - v_{ij}^2)$	S^-	**C**	**Rank**
50184	0.0094	0.0969	0.0010	0.0321	0.2491	39
50613	0.0096	0.0982	0.0005	0.0213	0.1785	116
50618	0.0094	0.0969	0.0009	0.0305	0.2396	48
50628	0.0096	0.0979	0.0005	0.0223	0.1856	113
50630	0.0094	0.0970	0.0011	0.0329	0.2532	35
51229	0.0095	0.0976	0.0005	0.0225	0.1871	109
51347	0.0094	0.0970	0.0014	0.0374	0.2784	22
51864	0.0058	0.0764	0.0043	0.0659	0.4632	8
51865	0.0097	0.0984	0.0004	0.0198	0.1674	126
51870	0.0096	0.0978	0.0006	0.0240	0.1968	91
51871	0.0094	0.0971	0.0009	0.0297	0.2343	52
52938	0.0094	0.0970	0.0005	0.0233	0.1934	96
52939	0.0097	0.0984	0.0003	0.0178	0.1529	129
52942	0.0084	0.0918	0.0013	0.0361	0.2824	21
52943	0.0084	0.0914	0.0019	0.0431	0.3204	20
53234	0.0100	0.1000	0.0002	0.0150	0.1305	135
53550	0.0101	0.1007	0.0002	0.0157	0.1349	132
53551	0.0095	0.0976	0.0006	0.0241	0.1982	89
53553	0.0095	0.0976	0.0008	0.0274	0.2195	64
54619	0.0090	0.0951	0.0006	0.0245	0.2050	80
54620	0.0059	0.0765	0.0040	0.0632	0.4525	18
54765	0.0102	0.1011	0.0002	0.0152	0.1306	134
55418	0.0095	0.0976	0.0004	0.0198	0.1689	125
55419	0.0093	0.0962	0.0007	0.0256	0.2102	74
55420	0.0096	0.0979	0.0004	0.0190	0.1627	127
55522	0.0095	0.0973	0.0011	0.0332	0.2542	33
55524	0.0094	0.0970	0.0011	0.0328	0.2525	36
55583	0.0092	0.0959	0.0006	0.0240	0.2004	88
91357	0.0095	0.0974	0.0005	0.0225	0.1877	107
91744	0.0097	0.0984	0.0004	0.0209	0.1754	119
91837	0.0094	0.0972	0.0005	0.0222	0.1857	112
91948	0.0099	0.0993	0.0003	0.0164	0.1420	131
92057	0.0096	0.0978	0.0006	0.0252	0.2048	82
92697	0.0097	0.0987	0.0005	0.0215	0.1789	115
92698	0.0042	0.0650	0.0043	0.0654	0.5013	3
95437	0.0095	0.0976	0.0012	0.0348	0.2627	30
95438	0.0098	0.0989	0.0002	0.0152	0.1331	133
95808	0.0046	0.0679	0.0052	0.0722	0.5153	2
95438_A	0.0094	0.0971	0.0006	0.0236	0.1956	93

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